THREE ESSAYS ON THE ECONOMIC IMPACT OF FUEL ECONOMY POLICIES

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Jianwei Xing

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Jianwei Xing, Ph.D.

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To reduce local air pollution and greenhouse gas emissions from the transportation sector, governments in the U.S. and elsewhere have introduced various policy instruments including taxes, subsidies, and technology standards to reduce oil consumption from passenger transport. My dissertation aims to empirically evaluate the cost-effectiveness of certain programs that intend to increase the fleet fuel economy including consumer subsidies for adopting alternative fuel vehicles (AVFs) and the Corporate Average Fuel Economy (CAFE) Standards imposed on manufacturers. The dissertation is comprised of three chapters. Chapter 1 studies the impact of income tax credit for electric vehicle (EV) purchases and compare its cost-effectiveness with an alternative policy that subsidies charging stations when indirect network effects exist in the market. Chapter 2 estimates consumer vehicle demand using random coefficient discrete choice model and examines the substitution pattern of EVs with other fuel types, which helps assessing the environmental benefits of policies that subsidize EVs. Chapter 3 investigates the differential treatment between light trucks and passenger cars in CAFE standards and estimates to what extent does the standard split undermine the policy goal of increasing the average fleet fuel economy while achieving the redistributional goals.

BIOGRAPHICAL SKETCH

Jianwei Xing was born in Nantong, Jiangsu Province, P. R. China on Nov. 25th, 1988. He participated in Sino-American 1+2+1 Dual Degree Program in 2008 and graduated from both Nanjing University of Information Science & Technology and George Mason University with a Bachelor of Science Degree in Economics. During his undergraduate study at George Mason University, he was on Deans List every semester and won Howard R. Block Memorial Award and The Economics Department Award for Outstanding Academic Achievement. In 2011, Jianwei was admitted by Master of Science program in the Dyson School of Applied Economics and Management at Cornell University. After two years of graduate studies, Jianwei developed his research interests in environmental and energy economics and industrial organization and continued to pursue a PhD degree in applied economics at Dyson School, under the supervision of Professor Shanjun Li. During the five years of the PhD program, Jianwei presented his research in various conferences including National Tax Association Annual Conference, AERE Annual Summer Conference and Northeast Workshop on Energy Policy and Environmental Economics. Jianwei and his coauthors published their research in the flagship journal in the environmental economics and his sole-authored paper was awarded Second Place for George F. Warren Award at Dyson School. Jianwei decides to pursue an academic career after obtaining his doctorate degree and he will join the National School of Development of Peking University as an assistant professor in Fall 2018.

This is dedicated to my family and friends.

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CHAPTER 1

INDIRECT NETWORK EFFECTS AND SUBSIDIES FOR ELECTRIC VEHICLES

1.1 Introduction

The electrification of the transportation sector through the diffusion of plug-in electric vehicles (EVs), coupled with cleaner electricity generation, is considered a promising pathway to reduce air pollution from on-road vehicles and to strengthen energy security. The U.S. transportation sector contributes to nearly 30% of U.S. total greenhouse gas emissions, over half of carbon monoxide and nitrogen oxides emissions, and about a quarter of hydrocarbons emissions in recent years. It also accounts for about three-quarters of U.S. petroleum consumption. Different from conventional gasoline vehicles with internal combustion engines, plug-in electric vehicles (EVs) use electricity stored in rechargeable batteries to power the motor and the electricity comes from external power sources. When operated in all-electric mode, EVs consume no gasoline and produce zero tailpipe emissions. But emissions shift from on-road vehicles to electricity generation, which uses domestic fuel source. The environmental benefit critically depends on the fuel source of electricity generation.[1]

Since the introduction of the mass-market models into the U.S. in late 2010, monthly sales of EVs have increased from 345 in December 2010 to 13,388 in December 2015.[2] Despite the rapid growth, the market share of electric cars is

[1]Holland et al.(2015) [48] find considerable heterogeneity in environmental benefits of EV adoption depending on the location and argue for regionally differentiated EV policy.

[2]From 1996 to 1998, GM introduced over 1000 first-generation EVs (EV1) in California, mostly made available through leases. In 2003, GM crushed their EVs upon the expiration of the leases.

still small: the total EV sales only made up 0.82% of the new vehicle market in 2015. In the 2011 State of the Union address, President Obama set up a goal of having one million EVs on the road by 2015. Based on the actual market penetration, the goal was met less than halfway.[3]

As a new technology, EVs face several significant barriers to wider adoption including the high purchase cost, limited driving range, the lack of charging infrastructure and long charging time. Although EV owners can charge their vehicles overnight at home, given the limited driving range, consumers may still worry about running out of electricity before reaching their destination. This issue of range anxiety could lead to reluctance to adopt EVs especially when public charging stations are scarce. At the same time, private investors have less incentive to build charging stations if the size of the EV fleet and the market potential are small. The interdependence between the two sides of the market (EVs and charging stations) can be characterized as indirect network effects (or the chicken-and-egg problem): the benefit of adoption/investment on one side of the market increases with the network size of the other side of the market.

The objective of this study is to empirically quantify the importance of indirect network effects on both sides of the EV market and examine their policy implications. This is important for at least two reasons. First, while industry practitioners and policy makers often use the chicken-and-egg metaphor to characterize the challenge faced by this technology, we are not aware of any empirical analysis on this issue. Examining the presence and the magnitude of indirect network effects is important in understanding the development of the EV market. If indirect network effects exist on both sides of the market, feed-

[3]Similar national goals exist in many other countries: Chinese government set up a goal of half a million EVs on the road by 2015 and five million by 2020. German government developed an initiative to reach one million EVs by 2020.

back loops arise. The feedback loops could exacerbate shocks, whether positive or negative, on either side of the market (e.g., gasoline price changes or government interventions) and alter the diffusion path. Ignoring feedback loops could lead to under-estimation of the impacts of policy and non-policy shocks in this market.

Second, indirect network effects could have important policy implications. As we describe below, policy makers in the U.S. and other countries are employing a variety of policies to support the EV market. When promoting consumer adoption of this technology, they can subsidize EV buyers or charging station investors or a combination of the two. Both our theoretical and empirical analysis show that the nature of indirect network effects largely determines the effectiveness of different policies. Therefore, understanding indirect network effects could help develop more effective policies to promote EV adoption.

Taking advantage of a rich data set of quarterly new EV sales by model and detailed information on public charging stations in 353 Metropolitan Statistical Areas (MSAs) from 2011 to 2013, we quantify indirect network effects on both sides of the market by estimating two equations: a demand equation for EVs that quantifies the effect of the availability of public charging stations on EV sales; and a charging station equation that quantifies the effect of the EV stock on the deployment of charging stations. Recognizing the endogeneity issue due to simultaneity in both equations, we employ an instrumental variable strategy to identify indirect network effects. To estimate the network effects of charging stations on EV adoption, we use Bartik (1991)-style instrument [7] for the endogenous number of electric charging stations, which interacts national charging station deployment shock with local market conditions: number of grocery stores and supermarkets. To estimate the network effects of EV stock on charging station deployment, we use current and historic gasoline prices to instrument for the endogenous cumulative EV sales. Across various specifications, our analysis finds statistically and economically significant indirect network effects on both sides of the market. The estimates from our preferred specifications show that a 10% increase in the number of public charging stations would increase EV sales by about 8% while a 10% growth in EV stock would lead to a 6% increase in charging station deployment.

With the parameter estimates, we examine the effectiveness of the federal income tax credit program which provides new EV buyers a federal income tax credit of up to $7,500.[4] Our simulations show that the $924.2 million subsidy program contributed to 40.4% of the total EV sales during this period. Importantly, our analysis shows that feedback loops resulting from indirect network effects in the market accounted for 40% of that sales increase, a significant portion. Our simulations further show that if the $924.2 million tax incentives were used to build charging stations instead of subsidizing EV purchase, the increase in EV sales would have been twice as large. The better cost-effectiveness of the subsidy on charging stations relative to the income tax credit for EV buyers is due to (1) strong indirect network effects on EV demand; and (2) low price sensitivity of early adopters.

This study directly contributes to the following three strands of literature. First, our study adds to the emerging literature on consumer demand for electric vehicles. Congressional Budget Office (CBO) [21] estimates the effect of

[4]Throughout our analysis, we treat the tax credit as a full-amount rebate due to the lack of household-level data in our analysis. EV buyers are more affluent than average vehicle buyers and their tax liability is likely to be over $7,500. According to California Plug-in Electric Vehicle Owner Survey (2014), among buyers of conventional new vehicles, 15% of households have annual household income over $150,000 while among EV buyers, that share is 54%.

income tax credits for EV buyers based on previous research on the effects of similar tax credits on traditional hybrid vehicles and finds that the tax credit could contribute to nearly 30% of future EV sales. DeShazo et al. (2014) [29] use a state-wide survey of new car buyers in California to estimate price elasticities and willingness to pay for different vehicles and then simulate the effect of different rebate designs. They estimate that the current rebate policy in California that offers all income classes the same rebate of $2,500 for BEVs and $1,500 for PHEVs lead to a 7% increase in EV sales. Using market-level sales data, our study offers a first analysis to quantify the role of indirect network effects in the market and their implications on government subsidies.

Second, our study fits into the rich literature on indirect network effects. Previous work on indirect network effects dates back to early theoretical studies such as Rohlfs (1974)[85], Katz and Shapiro (1985)[57] and Farrell and Saloner (1985) [36]. Our paper is also related to the emerging literature on two-sided markets that exhibit indirect network effects[5]. Theoretical work includes Rochet and Tirole (2006) [84], Caillaud and Jullien (2003) [20], Armstrong (2006)[5], Hagiu (2006) [45], and Weyl (2010) [96], and empirical work includes the PDA and compatible software market by Nair et al. (2004) [76], the market of CD titles and CD players by Gandal et el.(2000) [40], the yellow page industry by Rysman (2004) [87], and the video game industry by Clements and Ohashi (2005) [24], Corts and Lederman (2009) [26], Lee (2013) [65], and Zhou (2014) [100]. In this strand of literature, our study is closest to Corts (2010) [25] in topic which extends the literature to the automobile market and studies the effect of the

[5] Although exhibiting indirect networks, the EV market differs from the canonical two-sided markets in that there is no well-defined platform for buyers and sellers to interact. The automakers sell EVs to consumers directly. Public charging stations serve as a backup to home charging (e.g., a complementary good). The automakers do not charge charging stations loyalty fees or membership fees as is often the case in a two-sided market.

installed base of flexible-fuel vehicles (FFV) on the deployment of E85 fueling stations. Corts (2010) [25] only focuses on indirect network effects on one side of the market and does not look at that the effect of E85 fueling stations on FFV adoption.

Third, our analysis contributes to the rich literature on the diffusion of vehicles with advance fuel technologies (e.g., hybrid vehicles) and alternative fuels (e.g., FFVs). Kahn (2007) [55], Kahn and Vaughn (2009) [56], and Sexton and Sexton (2014) [89] examine the role of consumer environmental awareness and signaling in the market for traditional hybrid vehicles. Heutel and Muehlegger (2012) [47] study the effect of consumer learning in hybrid vehicle adoption focusing on different diffusion paths of Honda Insight and Toyota Prius. Several recent studies have examined the impacts of government programs both at the federal and state levels in promoting the adoption of hybrid vehicles including Beresteanu and Li (2011) [11], Gallagher and Muehlegger (2011) [39] and Sallee (2011) [88]. Both hybrid vehicles and EVs represent important steps in fuel economy technology. Environmental preference, consumer learning and government policies are likely to be all relevant in the EV market. Our paper focuses on the key difference between these two technologies: indirect network effects in the EV market. Huse (2014) [50] examines the impact of government subsidy in Sweden on consumer adoption of FFVs and the environmental impacts when consumers subsequently choose to use gasoline instead of ethanol due to low gasoline prices. Based on naturalistic driving data, Langer and McRae (2014) [62] show that a larger network of E85 fueling stations would reduce the time cost of fueling and hence increase the adoption of FFVs.

Section 1.2 briefly describes the industry and policy background of the study and the data. Section 1.3 presents a simple model of indirect network effects and uses simulations to show how feedback loops amplify shocks. Section 1.4 lays out the empirical model. Section 1.5 presents the estimation results. In section 1.6, we present the policy simulations and compare the existing income tax credit policy with an alternative policy. Section 1.7 concludes.

1.2 Industry and Policy Background and Data

In this section, we first present industry background focusing on important barriers to EV adoption and then discuss current government policies. Next we present the data used in the empirical analysis.

1.2.1 Industry Background

Tesla Motors played a significant role in the come-back of electric vehicles by introducing Tesla Roadster, an all-electric sport car in 2006 and beginning general production in March 2008. However, the model had a price tag of over $120,000, out of the price range for average buyers. Nissan Leaf ($33,000) and Chevrolet Volt ($41,000) were introduced into the U.S. market in December 2010, marking the beginning of the mass market for EVs.

There are currently two types of EVs: battery electric vehicles (BEVs) which run exclusively on high-capacity batteries (e.g., Nissan LEAF), and plug-in hybrid vehicles (PHEVs) which use batteries to power an electric motor and use another fuel (gasoline) to power a combustion engine (e.g., Chevrolet Volt). As depicted in Figure 1.1, quarterly EV sales increased from less than 2,000 in the first quarter of 2011 to nearly 30,000 in the last quarter of 2013 while the number of public charging stations has increased from about 800 to over 6,000. Nevertheless, the EV market is still very small: EV sales only made up 0.82% (or 113,889) of the total new vehicle sales in the U.S. in 2015 and there are only about 12,500 public charging stations as of March 2016, compared to over 120,000 gasoline stations.

There are several commonly-cited barriers to EV adoption. First, EVs are more expensive than their conventional gasoline vehicle counterparts. The manufacturer's suggested retail prices (MSRP) for the 2015 model of Nissan Leaf and Chevrolet Volt are $29,010 and $34,345, respectively, while the average price for a comparable conventional vehicle (e.g., Nissan Sentra, Chevrolet Cruze, Ford Focus and Honda Civic) is between $16,000 and $18,000. A major reason behind the cost differential is the cost of battery. As the battery technology improves, the cost should come down. In addition, lower operating costs of EVs can significantly offset the high initial purchase costs.[6] A recent study by EPRI (2013) compares the lifetime costs (including purchase cost less incentives, maintenance, and operation) of vehicles of different fuel types and finds that under reasonable assumptions, higher capital costs are well balanced by savings in operation costs: EVs are typically within 10% of comparable hybrid and conventional gasoline vehicles.

The second notable barrier to EV adoption is the limited driving range. BEVs have a shorter range per charge than conventional vehicles have per tank of gas, contributing to consumer anxiety of running out of electricity before reaching a

[6]For a regular EV such as Nissan Leaf, the fuel cost of traveling 100 miles is about $3.6 assuming that it takes 30 kWh to drive the distance and the electricity price is 12 cents per kWh. For a conventional gasoline vehicle, the fuel cost is about $14 assuming the fuel economy of 25 MPG and gasoline price at $3.5 per gallon.

charging station. Nissan LEAF, the most popular BEV in the U.S. has an EPA-rated range of 84 miles on a fully charged battery in 2015. Chevrolet Volt has an all-electric range of 38 miles, beyond which it will operate under gasoline mode. This range is sufficient for daily household vehicle trips but may not be enough for longer distance travels.

The third barrier, closely related to the second, is the lack of charging infrastructure. A large network of charging stations can reduce range anxiety and allow PHEVs to operate more under the all-electric mode to save gasoline.[7] There are two types of public charging stations: 240 volt AC charging (Level 2 charging) and 500 volt DC high-current charging (DC fast charging), with the former being the dominant type. The installation of charging stations involves a variety of costs including charging station hardware, other materials, labor and permit. A typical Level 2 charging station for public use has 3-4 charging units and costs about $ 27,000 while a DC fast charging station costs over $50,000.[8] Charging stations can be found at workplace parking lots, shopping centers, grocery stores, restaurants, dealers and existing gasoline stations, a point that we will come back to when constructing the instrument for the number of charging stations in the EV demand estimation. Owners of charging stations are often motivated by a variety of considerations such as boosting their sustainability credentials, attracting customers for their main business, and providing a service for employees. Charging stations are often managed by one of the major

[7]According to California Plug-in Electric Vehicle Owner Survey (2014), 71% of EV owners expressed dissatisfaction with public charging infrastructure, coming down from 83% in 2012.

[8]According to the charging station cost report by U.S. Department of Energy Vehicle Technologies Office (2015), the cost of a level-2 EV charging unit for public use is between $3,000 and $6,000, and the installation fee is from $600 to $12,700 per unit. Use the average equipment cost ($ 4,500) and installation fee ($3,000) per unit, the total cost of installing a charging station of an average size (3.6 charging units) comes at $27,000. This estimate does not include future maintenance and operating cost and is therefore a lower bound estimate. Footnote 28 provides a upper bound estimate which includes those costs.

national operators such as Blink, ChargePoint, and eVgo.

The fourth barrier is the long charging time. It takes much longer to charge EVs than to fill up gasoline vehicles. A BEV may not be able to get fully charged overnight if just using a regular 120 Volt electric plug (e.g., it takes 21 hours for Nissan LEAF to get fully charged). To get faster charging, BEV drivers either need to install a charging station at home or go to public charging stations. It takes 6-8 hours to fully charge a Nissan Leaf at a Level 2 charging station and only 10-30 minutes at a DC fast charging station.[9] Unlike BEVs, PHEV batteries can be charged not only by an outside electric power source, but by the internal combustion engine as well. Having the second source of power may alleviate range anxiety but the shorter electric range limits the fuel cost savings from EVs.

1.2.2 Government Policy

The diffusion of electric vehicles together with a clean electricity grid can be an effective combination in reducing local air pollution, greenhouse gas emissions and oil dependency. The EV technology is widely considered as representing the future of passenger vehicles. The International Energy Agency projects that by 2050, EVs have the potential to account for 50% of the light duty vehicle sales.[10] Many countries around the world have developed goals to develop the EV market and provide support to promote the diffusion of this technology

[9]Consumers do not need to wait for the battery to get fully charged before operating their vehicles again. They can recharge batteries by a certain amount depending on the duration of their stay at the charging locations while working, shopping or running errands. Public charging stations mainly serve as a backup or complementary charging option to alleviate EV drivers' range anxiety. A concern towards DC fast charging is that it can reduce battery life due to the nature of charging. In addition, DC fast charging on a large scale can create demand spikes on the local electricity grid and exacerbate peak demand.

[10]Hydrogen vehicles (not yet mass-produced) will account for the majority of the remainder.

[74].[11]

To reduce the price gap between EVs and their gasoline counterparts, the Energy Improvement and Extension Act of 2008, and later the American Clean Energy and Security Act of 2009 grant federal income tax credit for new qualified EVs. The minimum credit is $2,500 and the credit may be up to $7,500, based on each vehicle's battery capacity and the gross vehicle weight rating. Moreover, several states have established additional state-level incentives to further promote EV adoption such as tax exemptions and rebates for EVs and non-monetary incentives such as HOV lane access, toll reduction and free parking. California through the Clean Vehicle Rebate Project offers $2,500 rebate to BEV buyers and $1,500 rebate to PHEV buyers. In addition, federal, state and local governments provide funding to support charging station deployment. For example, the Department of Energy provided ECOtality Inc. $115 million grant to build residential and public charging stations in 22 U.S. cities in collaboration with local project partners.

Government intervention in this market could be justified from the following perspectives. First, indirect network effects in the EV market represent a source of market failure since the marginal consumer/investor only consider the private benefit in their decision and the network size on both sides is less than optimal [71] [23]. In addition, given the nature of the market, each side of the market is unlikely to internalize the external effect on the other side through market transactions. If EVs are produced by one automaker, the automaker would have incentive to offer a charging station network to increase EV adoption. Nissan and GM are the two early producers of EVs but more and more

[11]The Chinese government provides rebate of over $9,000 to BEV buyers and nearly $8,000 for PHEV buyers. The UK government offers a grant of up to $7,800 to EV buyers. In Japan, EV buyers were eligible for a subsidy of up to $10,000 in 2013 and $8,500 in 2014.

auto makers are entering the competition. Nissan is a large owner of charging stations but GM is not.[12]

Second, the external costs from gasoline consumption in the U.S. and many countries around the world are not properly reflected by the gasoline tax [80] [79]. Compared to conventional gasoline vehicles, EVs offer environmental benefits when the electricity comes from clean generation such as renewables. In regions that depend heavily on coal or oil for electricity generation, EVs may not demonstrate an environmental advantage over gasoline vehicles.[13] The electricity generation continues to become cleaner around the world due to the adoption of abatement technologies (e.g., scrubbers), the deployment of renewable generation and the switch from coal to natural gas. In addition, technologies are being developed to integrate EVs and renewable electricity generation such as solar and wind. The integration of the intermittent energy source with EV charging not only can help EVs fully realize its environmental benefits but also can leverage EV batteries as a storage facility to address the issue of intermittency and serve as energy buffer [72].

Third, technology spillovers among firms often exist especially in the early stage of new technology diffusion [93]. The development of the EV technology requires significant costs but the technology knowhow once developed can spread through many channels including worker migration and the product

[12]Tesla is building its own proprietary network for Telsa owners only. This suggests that they recognize the importance of charging stations in EV adoption but this would create duplicate systems.

[13]Zivin et al. (2014) [101] estimate marginal CO_2 emissions of electricity production that vary by location and time of the day and they find that charging EVs in some regions (the upper Midwest) during the recommended off-peak hours of midnight to 4am even generates more carbon emissions than the average conventional gasoline vehicle on the road. The environmental benefit of EVs under different fuel mix of electricity generation is still an active research topic and a critical element that has not been well understood in the literature is what types of vehicles (hybrid or gasoline vehicles) EVs replace.

market. Bloom et al.(2013) [16] estimate that the social returns to R&D are larger than the private returns due to positive technology spillovers, implying under-investment in R&D. In addition, the social returns to R&D by larger firms are larger due to stronger spillovers.

1.2.3 Data

We construct a panel dataset consisting of quarterly EV sales by vehicle model and the number of charging stations available at 353 MSAs from 2011 to 2013. Table 1.1 presents summary statistics of the variables used in our regression analysis. Data on quarterly vehicle sales of each EV model in each MSA is purchased from IHS Automotive. The sales data include 17 EV models: 10 BEVs and 7 PHEVs. Due to different introduction schedules, there were two vehicle models in our 2011 data: Nissan LEAF and Chevrolet Volt. The 2012 data include four more vehicle models: Ford Focus EV, Mitsubishi i-MiEV, Fisker Karma, and Toyota Prius Plug-in. The 2013 data include 11 additional models: Honda Accord Plug-in, Ford C-Max Energi, Cadillac ELR, Honda Fit EV, Fiat 500E, Smart ForTwo Electric Drive, Tesla Model S, Porsche Panamera, Toyota RAV4, Chevrolet Spark EV, and Ford Transit Connect EV. In 2013, the top four EV models are Nissan Leaf, Chevrolet Volt, Tesla Model S and Toyota Prius plug-in with market shares (sales) of 25.8% (22,610), 24.4% (23,094), 17.4% (18,650) and 9.4% (12,088), respectively.

For our analysis, we focus on the 353 MSAs (out of 381 MSAs in total) for which observations are available in all three years, and their EV sales accounted for 83% of the national EV sales during our data period. Panel A of Figure

1.1 depicts the spatial patten of EV ownership (the number of EVs per million people) in the last quarter of 2013. It shows that large urban areas have a higher concentration of EVs. The MSA with the highest concentration is San Jose-Sunnyvale-Santa Clara, CA with 5,608 EVs per million people by the end of 2013. The next two MSAs are both nearby: San Francisco-Oakland-Fremont and Santa Cruz-Watsonville. The MSA with the lowest concentration is Laredo, TX with only 36 EVs per million people (9 EVs with a population of a quarter of a million).

We obtain detailed information on locations and open dates of all charging stations from the Alternative Fuel Data Center (AFDC) of the Department of Energy. By matching the ZIP code of each charging station to an MSA and using the station open date, we construct the total number of public charging stations available in each quarter for each MSA. Panel B of Figure 1.2 shows the spatial distribution of charging stations (the number of charging stations per million people). The pattern is very similar to what we observe in Panel A for EV ownership. The correlation coefficient between the two variables is 0.63, partly reflecting the interdependence of EVs and charging stations. The top three MSAs with the most charging stations per million people are Corvallis, OR, Olympia, VA and Napa, CA with 210, 170, 117 public charging stations per million people, respectively. These three MSAs are the number 11th, 5th, and 6th in terms of the EV concentration in Panel A.

We collect data on state-level incentives such as tax credits and rebates for both electric vehicles and charging stations from AFDC. From the American Chamber of Commerce cost-of-living index database, we collect quarterly gasoline prices for each MSA from 2008 to 2013. Household demographics are collected from the American Community Survey.

1.3 A Model of Indirect Network Effects

In this section, we use a stylized model to illustrate indirect network effects on both sides of the market (EV demand and charging station investment) and to show how indirect network effects give rise to feedback loops. We then conduct simulations to shed light on how the effectiveness of different types of policies (e.g., subsidizing EV purchases versus charging station investment) hinges on the relative magnitude of indirect network effects on the two sides as well as consumer price sensitivity. The results from the simulations provide theoretical basis for our empirical findings based on real-world data.

1.3.1 Model Setup and Properties

We assume that EV sales $q_t(N_t, p_t, x_t)$ depends on the number of public charging stations in the market (N_t), the price of EV (p_t) and other product characteristics combined (x_t) that affect consumers' choice such as the fuel cost.[14] The installed base of EVs is the cumulative sum of EV sales minus scrappage by the time t, denoted by $Q_t = \sum_{h=1}^{t} q_h * s_{t,h}$, where $s_{t,h}$ is the survival rate at time t for EVs sold in time h. The number of charging stations that have been built $N_t(Q_t, z_t)$ depends on the EV market size Q_t and other variables combined z_t that might affect the fixed cost of investment. To facilitate the illustration, we specify the

[14] We assume there is only one EV model to ease exposition. Our empirical analysis is at the vehicle model level and uses a richer specification.

following functions for EV demand and charging station deployment:

$$ln(q_t) = \beta_1 ln(N_t) + \beta_2 ln(p_t) + \beta_3 x_t, \tag{1.1}$$

$$ln(N_t) = \gamma_1 ln(Q_t) + \gamma_2 z_t. \tag{1.2}$$

The EV demand equation arises from a discrete choice model of vehicle demand and follows closely the logit model using the market-level data as in [12]. The charging station equation can be derived from an entry model as in [40] and we derive an empirical counterpart to this equation for our specific context in the appendix.

β_1 and γ_1 capture the magnitude of the indirect network effects on the two sides. Feedback loops (or two-way feedback) arise if both β_1 and γ_1 are non-zero. Intuitively, a shock to the system, for example an increase in x_t would change EV sales q_t, which would in turn affect the installed base Q_{t+1}. This would then lead to changes in the number of charging stations N_{t+1} and hence affect q_{t+1}. The impact would circle back and forth between these two equations. If both β_1 and γ_1 are positive, positive feedback loops would arise and they can amplify the shocks (either positive or negative) in either side of the market such as tax credit for EV purchases or subsidy on charging station investment. β_2 (negative) is the price elasticity of demand and captures consumer price sensitivity.

To understand the property of the system such as the existence of the steady state and its property, we assume that the survival rate $s_{t,h}$ is δ^{t-h}, where $\delta < 1$. Further assume $p_t = p, x_t = x$ and $z_t = z$. Substituting equation (2) into equation (1), we have:

$$ln(q_t) - \beta_1\gamma_1 ln(q_t + \delta Q_{t-1}) = \beta_1\gamma_2 z + \beta_2 ln(p) + \beta_3 x. \tag{1.3}$$

The right-hand side $\beta_1\gamma_2 z + \beta_2 ln(p) + \beta_3 x$ is constant with respect to q_t and we denote it by c. During period 1, $Q_{t-1} = 0$. Solving the equation, we obtain $q_1 = exp(\frac{c}{1-\beta_1\gamma_1})$. To solve for the steady state solution (q^*, N^*), we use the steady state condition $q_t = q_{t+1} = q^*$ and find:

$$q^* = exp(\frac{c - \beta_1\gamma_1 ln(1-\delta)}{1-\beta_1\gamma_1}) = q_1 * exp(\frac{-\beta_1\gamma_1 ln(1-\delta)}{1-\beta_1\gamma_1}).$$

$$N^* = exp[\gamma_1 \frac{c - \beta_1\gamma_1 ln(1-\delta)}{1-\beta_1\gamma_1} - \gamma_1 ln(1-\delta) + \gamma_2 z].$$

The stock of EVs in the steady state $Q^* = q^*/(1-\delta)$ where the outflow of EVs due to scrappage is equal to the inflow from new EV sales.[15] To examine the stability of the steady state, we write $Q_{t-1} = q_{t-1} + \delta Q_{t-2}$ and substitute it into equation (3): $ln(q_t) - \beta_1\gamma_1 ln(q_t + \delta q_{t-1} + \delta^2 Q_{t-2}) = c$. This defines an implicit function of $q_t = G(q_{t-1})$. When $\beta_1\gamma_1 < 1$, it can be shown that $G(0) > 0, G'() > 0$, and $G''() < 0$. Therefore, the steady state solution is stable as shown in Figure 1.3. In our following policy analysis, we take $\beta_1\gamma_1 < 1$, which is also confirmed in our empirical analysis.

The partial effect of vehicle price p on EV sales in the steady state is:

$$\frac{\partial q^*}{\partial p} = exp(\frac{c - \beta_1\gamma_1 ln(1-\delta)}{1-\beta_1\gamma_1}) \frac{\beta_2}{1-\beta_1\gamma_1},$$

where $\beta_2 < 0$. When $\beta_1\gamma_1 < 1$, this partial effect is negative as economic theory would suggest. Similarly, the changes in other demand side factors captured by x and the changes in the factors in the charging station equation z will both shift

[15] Alternatively, the steady state can be equivalently expressed in terms of (Q^*, N^*). Our specification rules out (0,0) as another steady state solution. Having multiple equilibria is often a signature property of two-sided markets with indirect network effects due to self-confirming expectations (e.g., [40]). From an empirical perspective, our specification is without loss of generality since the empirical studies in this literature often assume that the non-zero stable solution plays out in the data.

$G(q_{t-1})$ in Figure 1.3 up or down and hence affect the steady state solution of EV sales.

1.3.2 Implications on Policy Choices

Now we conduct simulations to understand how feedback loops magnify policy shocks and their implications on policy choices. We fix p_t, x_t, and z_t in equations (1.1) and (1.2) and assume certain values for model parameters as reported in Table 1.2. We then solve for q_t, Q_t, and N_t sequentially for each period. Because of the positive feedback loops (by assuming both β_1 and γ_1 being positive), EV sales and the number of charging stations will keep growing naturally until they reach the steady state where the inflow of new vehicles equals the outflow of vehicles due to scrappage. To examine how positive feedback loops could amplify a policy shock, we simulate a scenario where all EV buyers are provided with a \$7,500 subsidy for the first five periods and no more subsidy is offered afterwards.

As shown in Panel (a) in Figure 1.4, due to both the price effect (captured by β_2) and the indirect network effects (captured by β_1 and γ_1), the subsidy increases EV sales substantially compared with the no-policy case during the first five periods. When the subsidy terminates, EV sales continue to increase through feedback loops but with a smaller magnitude. The sales increase due to subsidy gets smaller as feedback loops diminish and the two growth paths eventually overlap. In both cases, the path of EV sales converges to the same steady state but the policy shock makes the system converge to the steady state more quickly: indirect network effects expedite this process through positive feedback loops.

Figure 1.4 Panel (b) depicts a similar pattern in the dynamic path of charging station deployment. With the positive policy shock on the EV purchase side, the stock charging stations increases quickly for the first five periods and continues to grow at a decreasing rate after the policy. It eventually converges to the same steady state as in the no-policy scenario. This two graphs demonstrate that feedback loops from indirect network effects magnify a shock to any side of the system and alter the convergence process on both sides.

The existence of indirect network effects on both sides of the market could have important policy implications. To foster the development of the EV market, policy makers can choose to subsidize consumers for EV purchase directly (policy 1) or to subsidize charging station investment (policy 2). We conduct simulations to examine the relative cost-effectiveness of these two policy options. Policy 1 provides EV buyers with a subsidy of \$7,500 per EV in the first five periods. Policy 2 uses the same account of total funding as in policy 1 to build charging stations. We compare the cumulative sales increase over time due to these two policies (with a 5% annual discount rate).[16]

To examine the implication of relative strength of indirect network effects on policy choices, we vary the ratio of β_1/γ_1 by holding β_1 constant while changing γ_1. Figure 1.5 depicts, for any given price sensitivity β_2 (say -1.5), as β_1/γ_1 increases (i.e., indirect network effects in EV demand become relatively stronger),

[16]For policy 1, we subtract the EV price by \$7,500 to simulate the counterfactual sales in the first five periods. The total expenditure of the subsidy policy is then calculated by multiplying \$7,500 with the total EV sales for the five periods. By assuming the cost of building one charging station to be \$27,000, we obtain the total number of charging stations that could be built with the same amount of funding. We assume that the investment occurs evenly each year over the first five periods and we add the number of charging stations that could be funded to N_t to simulate the counterfactual outcomes under policy 2.

the second policy (subsidy on charging stations) becomes more and more effective measured by the increase in cumulative sales over time. The two policies are equivalent when β_1/γ_1 is 1 given the price elasticity of -1.5.

In addition to relative strength of indirect network effects on both sides, the policy comparison also depends on the price elasticity of EV demand. When consumers are more sensitive to prices (e.g., going from -1.5 to -1.6), the policy of subsidizing charging stations becomes relatively less effective for a given β_1/γ_1. This finding is illustrated by the outward shift of the curve when the price elasticity changes to -1.4 and -1.6. The result is intuitive: if consumers are less price-sensitive, it would take a larger subsidy on EV purchases in order to push consumers to buy EVs, hindering the effectiveness of the policy.

To summarize, the policy of subsidizing charging stations becomes more effective relative to the policy of subsiding EV purchases when indirect network effects on the EV demand become stronger (holding network effects on the charging station side constant) or when consumers are less sensitive to price. These findings offer a theoretical foundation for the policy comparison after our empirical analysis.

1.4 Empirical Framework

To investigate indirect network effects on both sides of the market, we estimate: (1) a EV demand equation that examines the effect of charging stations on EV sales; and (2) a charging station equation that estimates the effect of EV fleet on charging station deployment. These equations build upon equations (1) and (2) in the theoretical model above.

1.4.1 EV Demand

To describe the empirical demand model of EVs, let k index an EV model such as Nissan Leaf and Chevrolet Volt, m index a market (MSA), and t index a year-quarter. We estimate the following equation:

$$ln(q_{kmt}) \quad = \quad \beta_0 + \beta_1 ln(N_{mt}) + \beta_2' X_{kmt} + T_t + \delta_{km} + \varepsilon_{kmt}, \tag{1.4}$$

where q_{kmt} is the sales of EV model k in market m and year-quarter t.[17] N_{mt} denotes the total number of public charging stations that have been built in the MSA by the end of a given quarter.[18] We use the number of charging stations instead of the total number of charging outlets to represent the availability of charging infrastructure but the qualitative findings remain if we use the number of charging units. $ln(N_{mt})$ captures the effect of charging stations on electric vehicle purchases and the log form allows the effect to be diminishing. X_{kmt} is a vector of related covariates including the effective purchase price, personal income and other control variables. The effective purchase price of a model is defined as the manufacturer's suggested retail price (MSRP) less the related subsidies (tax credits and tax rebates at both federal and state levels).

We also include a full set of year-quarter (e.g., the first quarter of 2011) fixed effects and MSA-model (e.g., Nissan Leaf in San Francisco) fixed effects in equation (1.4). Year-quarter fixed effects T_t control for national demand shock for EVs common across MSAs such as consumer awareness. MSA-model fixed ef-

[17]This empirical specification is taken to be consistent with our theoretical model and to ease results interpretation. The logit model from Berry (1994) implies that the dependent variable would be $ln(s_{kit}) - ln(s_{0mt})$ where s_{kmt} is the market share of model k in market m and time t and s_{0mt} is the share of consumers who are not purchasing an EV. These two specifications provide almost identical parameter and elasticity estimates (see Table 1.6).

[18]In the estimation, we add one to q_{kmt}, N_{mt} to deal with zero values for some of the observations. Our results are robust to excluding observations with zero values on q_{kmt} or N_{mt} and using $ln(q_{kmt})$ and $ln(N_{mt})$.

fects δ_{km} not only control for time-invariant product attributes such as quality and brand loyalty that could affect vehicle demand but also control for time-invariant local preference for green products [55, 56] and demand shocks for each model (e.g., a stronger preference or dealer presence for Nissan Leaf in San Francisco). ε_{kmt} is the unobserved demand shocks that are time-varying and market-specific (for example, unobserved local government subsidy for purchasing EVs or market-specific promotions for a vehicle model that vary over time).

It is well documented in the vehicle demand literature that failing to control for unobserved product attributes could lead to downward bias in the price coefficient estimates (for example [13]; [11]). MSA-model fixed effects absorbs both observed and unobserved vehicle attributes variations which are time-invariant and what is left is the variation of vehicle attributes over time. Since most of the EV models in our sample appear for only one year and there is little variation of the observed attributes for the models that appear for more than one year, we believe that using MSA-model fixed effects could control for unobserved product attributes and alleviate the need to use the methodology developed in Berry et al. (1995) [13] to deal with price endogeneity where they only have national-level sales data (i.e., one market).[19] The price coefficient is identified from the fact that effective EV prices vary across markets and over time due to state-level subsidies and temporal price variations.

Although we include a rich set of control variables, the charging station vari-

[19]The methodology in Berry et al. (1995) [13] uses a contracting mapping technique to first back out product-level fixed effects (mean utility) in the first stage and then uses IV strategy to estimate the remaining preference parameters based on the assumption that observed product attributes are not correlated with observed product attributes, which could be a strong assumption [60]. As a robustness check, we also include electric range and electric mpg in one of the alternative specifications and the results are qualitatively the same.

able is still endogenous due to simultaneity: the unobserved time-varying and market-specific demand shocks could affect charging station investment decisions and hence the stock of charging stations. To deal with the endogeneity, we use the IV strategy and a valid IV needs to be correlated with the number of charging stations in an MSA (the endogenous variable) but not correlated with the unobserved shocks to EV demand. The IV we employ is the interaction term between the number of grocery stores and supermarkets in an MSA in 2012 with the number of charging stations in all MSAs other than the MSA corresponding to a given observation (lagged for one quarter). Grocery stores and supermarkets are a major owner of charging stations and they build charging stations to attract customers and boost green credentials among other reasons. These places could be good sites for public charging stations because EV drivers can charge their vehicles while shopping. Nissan has been actively partnering with grocery store owners to build charging stations. Kroger, the country's largest grocery store owner has installed about 300 charging stations in their stores across the country. Our data show that the number of grocery stores in an MSA is positively correlated with the number of charging stations.

However, the number of grocery stores does not vary with time in our sample period and it is therefore absorbed by the MSA fixed effects. To introduce temporal variation, we multiply it with the lagged number of existing charging stations in all MSAs other than the MSA corresponding to a given observation, which captures the national-level trend in charging station investment due to aggregate shocks such as temporal variations in costs, investor confidence and federal incentive programs. The construction of this IV is similar in spirit to the Bartik instrument used in the labor literature to isolate local labor demand changes [7]. The intuition for the IV is that national shocks to charging station investment (captured by the lagged number of charging station in all MSAs other than own) have disproportional effects on charging station investment across MSAs: MSAs with a larger number of grocery stores and supermarkets (hence better endowment of good sites for charging stations) will be affected by these national shocks more than others, leading to variations in charging stations across MSAs. Our first-stage results in Table 1.4 to be discussed below show that the interaction term has a positive and highly statistically significant impact on charging station investments.

We argue that this instrument should satisfy the exogeneity assumption. The number of grocery stores and supermarkets is unlikely to affect EV sales directly. There might be common unobservables that influence both the EV sales and the number of grocery stores, especially at the cross-sectional level. However, our model controls for MSA fixed effects and should capture these time-invariant unobservables. At the temporal dimension, EV sales vary from year to year but the number of grocery stores is very stable given the maturity of the industry. In fact, the number of grocery stores is measured at the end of 2012. The temporal variation in the IV comes from the total (lagged) number of charging stations in all MSAs other than the own city. Time fixed effect would control for time-varying common shocks across MSAs. Excluding home city's charging stations also removes the concern that one MSA's installation of large amount of charging stations could overly influence the estimation results.

Our IV strategy leverages the interaction term between a national-level variable with only temporal variation and a MSA-level variable with only spatial variation. The rationale behind the IV is that different MSAs have different pre-existing conditions/ability to absorb national shocks to charging station investment such as changes in macro-economic conditions and costs. One might be concerned that different MSAs may have different susceptibility to unobservable demand shocks at the national level and the number of grocery stores could be correlated with this susceptibility for some reason. To address this concern, we include a variety of MSA-level controls interacting with the time trend. We use the sales of hybrid vehicles in 2007 (several years before EVs entered the market) to proxy for preference heterogeneity for greener vehicles or environmental friendliness. We also include personal income, the share of college graduates among residents, the share of commuters driving to work, the share of commuters using public transport to work, and the share of white residents. We use the interactions of these variables with the time trend to control for potential heterogeneity in diffusion path of EVs across MSAs. Our results are robust to the inclusion of these controls, providing further support that our IV is a valid exclusion restriction.

In some of the robustness checks, we use local policy variables such as subsidies on charging stations as additional IVs and obtain similar results. We do not use them in our benchmark specifications due to the concern that local policies whether subsidizing charging stations or EV purchases could be a response to local unobserved demand shocks and hence be endogenous.

1.4.2 Charging Station Deployment

We derive the empirical model of charging stations investment from an entry model presented in the Appendix where the profit depends on both the installed base of EVs and the total number of charging stations in a market. Under certain functional form assumptions, the total number of charging stations in a free-entry equilibrium is given by the following equation:

$$ln(N_{mt}) \quad = \quad \gamma_0 + \gamma_1 ln(Q^{EV}_{mt}) + \gamma_2' Z_{mt} + T_t + \varphi_m + \varsigma_{mt}, \tag{1.5}$$

where N_{mt} denotes the stock of public charging stations that have been built in market m by time t and Q^{EV}_{mt} denotes the installed base of EVs by time t. The vector of covariates Z_{mt} include the state-level tax credit given to charging station investors measured as the percentage of the building cost, a dummy variable indicating whether there exists public grants or funding to build charging infrastructure, the interaction term of number of grocery stores in a MSA in 2012 with the lagged number of charging stations in all MSAs other than own (the instrument in the EV demand equation), and other control variables.

We also include a full set of time and MSA fixed effects. T_t denotes year-quarter fixed effects to control for time-varying common shocks to charging station investment across MSAs such as macro-economic conditions. Market fixed effects φ_m control for time-invariant and MSA-specific preferences for charging stations. For example, some MSAs may be "greener" than others and invest more on alternative fuel infrastructure. Similarly, MSAs with a higher population density and limited private installment of charging stations may have more public charging stations. ζ_{mt} is the unobserved shock to charging station investment, for instance, the unobserved local policies to support the charging station building. In the estimation, we add one to N_{mt} and Q^{EV}_{mt} to deal with zero values for some of the observations. We obtain similar results by dropping these observations and use $ln(N_{mt})$ and $ln(Q^{EV}_{mt})$ instead.

The issue of endogeneity due to simultaneity also arises in this equation. Both N_{mt} and Q^{EV}_{mt} are stock variables but the inflows to each variable are determined at the same time. As a result, time-varying and MSA-specific shocks to investment decisions (the error term in the equation) could be correlated with current EV sales which is part of the installed base. The instrument variables emerge more naturally in this equation. In particular, we instrument for the installed base of EVs with a set of current and past gasoline price variables. The fuel cost savings from driving EVs depend on the price difference between gasoline and electricity, which varies across locations. In MSAs with higher gasoline prices, consumers may have a stronger incentive to purchase EVs [20]. Because the installed base of EVs is the cumulative sales of EVs, we include gasoline prices not only in the current quarter but annual gasoline prices in the past three years as instruments. For example, for the installed base of EVs in the 2nd quarter in 2013, we use the gasoline price in the 2nd quarter in 2013, the average gasoline price in 2012, the average gasoline price in 2011, and the average gasoline price in 2010 as instrumental variables.

These gasoline price variables (including current and past gasoline prices) should affect the installed base, which is confirmed in the first-stage regression in Table 1.8 to be discussed below. But they are unlikely to affect investment decisions directly (i.e., other than through the installed base). Since we include both time and MSA fixed effect, the remaining variation in gasoline prices is largely driven by how time-varying crude oil prices interact with market conditions that are likely time-invariant during our data period (e.g., market structure in wholesale and retail gasoline markets and distance to refineries). These interactions lead to time-varying and MSA-specific differences in gasoline prices, which are unlikely to be correlated with charging station investment directly.

[20] A report on the ownership cost of EVs by Electric Power Research Institute (2013) finds that the increases and decreases in gasoline prices will have a significant impact on the relative costs of PEVs.

The decision of charging station investment hinges on, among other things, the EV market potential (proxied by the installed base of EVs) and the fixed costs of investment. Fixed costs of charging station investment include the cost of equipment (chargers) and labor cost, neither of which is likely to be correlated with gasoline price variations (after controlling for MSA and time fixed effects). The operating costs of the charger largely depend on electricity prices. There is no direct link between electricity and gasoline prices (after controlling for common shocks such as national economic conditions using time fixed effects).

1.5 Estimation Results

We first present parameter estimates for equation (1.4) and (1.5). We then discuss the indirect network effects implied by these parameter estimates.

1.5.1 Regression Results for EV Demand

Columns (a) to (e) in Table 1.3 report the ordinary least squares (OLS) estimation results for five different specifications where we add more control variables successively. Column (a) includes only six explanatory variables. Column (b) adds in year-quarter fixed effects to control for time-varying common unobservables across MSAs. Column (c) further adds vehicle model fixed effects to control for unobserved product attributes such as quality and brand loyalty that affect consumer demand. Column (d) includes rich MSA-model fixed effects to control for both unobserved product attributes and MSA-specific demand shocks for different EV models. Column (e) adds two additional variables to control for potential heterogeneity in the diffusion pattern across MSAs. The first variable is the interaction term between the sales of hybrid vehicles in 2007 (to proxy for preference for green vehicles) and the time trend and the second variable is the interaction between average personal income and the time trend. Column (f) implements a GMM estimation strategy and uses the interaction term of number of grocery stores and supermarkets in a MSA in 2012 with the lagged number of charging stations in all the other MSAs as the instrument for the number of charging stations.

Given the log-log specification, the coefficient estimates can be interpreted as elasticities. All the specifications provide intuitive and statistically significant coefficient on the key variables of interests: EV demand increases with a larger network of charging stations, a lower vehicle price, and more home charging stations funded by the EV project supported by the DOE, and higher income. The coefficient on the charging station variable captures indirect network effects from charging station investment on EV demand. The GMM results show that a 10% increase in charging stations would result in a 8.4% increase in the EV sales, which is higher than all the OLS estimates (ranging from 1.8% to 5%). This suggests that the number of charging stations is negatively correlated with the unobserved shocks to EV demand, leading to downward bias in OLS. One example of unobserved shocks is local EV incentives that local governments provide to compensate for the lack of public charging stations. Another example is the home charging incentives from local electric utilities. Many local utilities offer a rebate for installing a home charging station and a discounted rate for home EV charging as part of the demand-side management program. Local governments often partner with local utilities to provide more generous home charging incentives when there is a lack of private investment in public charging stations.

The price coefficients changes from -0.470 to -0.817 from columns (b) to (c) after vehicle model fixed effects are included. This is consistent with our discussion above: vehicle model fixed effects control for unobserved product attributes which could be positively correlated with prices. Ignoring unobserved product attributes will bias the price coefficient toward zero. Going from Columns (c) to (d) where MSA-model fixed effects are included, the EV demand function changes from being inelastic with an price elasticity of -0.817 to being elastic with a price elasticity of -1.378. MSA-model fixed effects control for MSA-specific time-invariant demand shocks (such as environmental preference) and these demand shocks could affect state-level tax incentives. For example, higher incentives are used to counter negative demand shocks. Hence MSA fixed effects could control for the potential endogeneity in state-level tax incentives. The GMM results provide a price elasticity of -1.288. Although this is at the lower end of the price elasticity estimates in the literature on automobiles, we believe that the magnitude is reasonable compared with the literature for two reasons.[21] First, EV buyers are more affluent and hence less price-sensitive compared with average vehicle buyers. Second and perhaps more importantly, EV buyers can be characterized as early adopters and one can argue that many of them choose EVs out of their strong environmental concerns and/or making a statement by driving an EV as has been documented in the case of hybrid vehicles (e.g., [55], and [89]).[22]

[21] Berry, Levinsohn and Pakes (1995) estimate the price elasticities ranging from -3 to -7 for vehicle models in 1990 with more expensive models having the smaller price elasticities (in magnitude). The lower end of price elasticities for vehicles models in 2006 in Beresteanu and Li (2011) is also around -3.

[22] California Plug-in Electric Vehicle Owner Survey (2014) shows that EV buyers have higher household income than buyers of gasoline vehicles and that the environmental concern is an important motivator for EV purchase. 38% of Nissan Leaf buyers and 18% Chevy Volt buyers consider the environmental concern to be the top motivator.

Lower fuel cost is one of the major benefits of EVs and higher gasoline prices will have a positive impact on EV adoption by increasing future fuel cost savings from driving EVs in place of conventional vehicles. To capture the heterogeneous impact of gasoline price on the demand of the two types of EVs, two interaction terms of quarterly gasoline prices with BEV and PHEV dummy variables are included. The results from all the specifications find a positive and statistically significant effect of gasoline price on BEV purchase. While the interaction term with PHEV is positive and significant in Columns (a) to (c), Columns (d) to (f) do not find a significant impact of gasoline price on PHEV demand when MSA-model fixed effects are included. Intuitively, BEV drivers could be more sensitive to gasoline prices than PHEV buyers given that BEV run exclusively on electricity while PHEVs run mostly on gasoline for long-distance driving given its short range of battery. That is, PHEV drivers do not make a long-term commitment to an alternative fuel to the extent that BEV drivers do. In addition to gasoline prices, we included electricity prices in previous analysis and the coefficient estimate was small in magnitude and statistically insignificant in all specifications. This could be due to: (1) the operating cost from using electricity is a small portion of vehicle lifetime cost for EVs; and (2) there is not much MSA-specific temporal variation in electricity prices. The coefficient on the interaction term between hybrid sales in 2007 and time trend is positive and statistically significant, implying that MSAs that had more sales of hybrid vehicles in 2007 (proxy for preference for greener products) have faster diffusion of EVs.

The results from these regressions imply that the increased availability of public charging stations has a statistically and economically significant impact on EV adoption decisions. Our estimation results confirm that even if most

EV drivers can charge vehicles at home, better access to public charging facilities elsewhere is still an important demand factor by, for example, alleviating range anxiety.[23] Based on the parameter estimates on charging station and price variables, a back-of-the-envelope calculation shows that the demand effect from having one more charging station from the sample average of 22.6 is equivalent to that from a reduction of EV price by $961 (the average price is $33,127). When the number of charging stations increases to 27.3 (the sample average in 2013), the equivalent price reduction is $795. At the sample maximum of 320 charging stations, one more charging station is only equivalent to $68 price reduction, showing the diminishing effect implied by the log-log functional form.

1.5.2 Alternative Specifications for EV Demand

We take the estimates in Column (f) in Table 1.3 as our baseline specification. To check the robustness of the results, we estimate a variety of different specifications and the results are reported in Table 1.5 & 1.6. Column (a) includes the interaction term between the number of charging stations and average commute time to work in the MSA to capture the heterogeneous impact of charging stations across cities with different commuting patterns.[24]. The positive coefficient estimate on the interaction term suggests that the availability of charging stations has a larger impact on EV demand in the MSAs with longer commute. This is intuitive since in MSAs where people have longer commute, range anxiety would be more of an issue. Across MSAs, the elasticity of charging stations

[23] According to the EV Project report (2013), the percentage of EV home charging for 22 program areas is about about 74% for Nissan Leaf and 80% for Chevrolet Volt.

[24] The average commute time to work at the MSA level is calculated based on combined 2006-2011 samples of American Community Survey. The average commute time is 22.96 with a standard deviation of 3.37, a minimum of 14.59 and maximum of 35.01

with respect to the EV sales ranges from 0.27 to 1.05 depending on the average commute time.

Column (b) adds the quadratic terms of the time trend variables to our baseline specification to allow more flexible time effect. The coefficient estimates on the key parameters are almost intact. Column (c) includes the interaction term of charging stations with a BEV dummy to capture the different impact of charging stations on BEVs and PHEVs. The coefficient estimate on the interaction term is positive while not statistically significant. Column (d) includes two more instruments: the tax credits and the availability of public funding for building charging stations, both of which appear in the charging station equation. We did not include them in our baseline specification because the exogeneity assumption may not hold for the subsidies as they could be a response to unobserved EV demand shocks. Column (e) removes the price variable in the regression to deal with the concern that the price variable especially state-level incentives could be endogenous. Column (f) adds the interaction terms between various demographic variables and the time trend to further control for MSA-level heterogeneity in the diffusion pattern. Across these specifications, the estimated effects of charging station availability on EV demand as well as other parameter estimates are similar to those from the baseline specification in Table 1.3. Column (g) reports the demand estimation using the logit model as in Berry (1994) and it produces almost identical elasticity estimates as our baseline specification.

Some states such as California and Oregon have adopted Zero Emission Vehicle program which requires a certain part of automakers' sales to be clean fuel vehicles and some automakers have introduced EV models in those regions only to comply with the regulations. To control for more intense competition in those markets due to more EV models introduced, Column (h) in Table 1.5 includes ZEV specific time fixed effects and the results are similar to previous results with a modest increase in the coefficient estimate on charging stations. Column(i) uses only BEV sales and the estimates are not systematically different from the estimates using the full sample with BEVs and PHEVs. Columns (j) and (k) increases the lag of the total number of charging stations in all other MSAs to 2 and 3 quarters when constructing the instrumental variable and there is no substantial change of the estimates except that the coefficient of the charging stations decreased slightly, primarily due to loss of observations. However, increasing the lag to more than three quarters leads to weak IV.

As shown in Column (g) in Table 1.6, our demand specifications would yield nearly identical results as the Berry-logit model. With only EV models in our data, our analysis treats all other non-EV models to be in one category (i.e., the outside good). Limiting the choice set and the substitution pattern across choices could potentially impact our estimate of the price elasticity and our policy simulations. EV models represent a different technology that is dramatically from conventional gasoline vehicles, therefore consumers are likely to consider them as a separate category in making purchase decisions especially given that the EV buyers in our data period are often motivated by strong environmental concern according to California Plug-in Electric Vehicle Owner Survey (2014). Nevertheless, some PHEVs do have conventional hybrid counterparts. For example, Toyota Prius-plug in has a hybrid version, Toyota Prius. Considering most of PHEVs have limited electric range (11-38 miles), some consumers may compare PHEVs with hybrid vehicles. Recognizing this, Column (i) in Table 1.6 only include BEV models in the regression. The results are very similar to those obtained using the full sample, suggesting that the limitation in our choice set and modeling framework may not have a large impact on the key parameters of interest.[25]

1.5.3 Regression Results for Charging Station Deployment

Columns (a) to (d) in Table 1.7 report the OLS regression results for the charging station equation (1.5). In Column (a), only the four explanatory variables of interest are included. Column (b) includes year-quarter fixed effects to control for time trends that are common to all MSAs such as federal subsidies for building charging stations that occur during a specific period of time. Column (c) further includes MSA fixed effects to control for time-invariant MSA-level baseline differences in charging station investment. Column (d) adds in the interaction term between the hybrid vehicle sales in 2007 (proxy for environmental friendliness) and time trend to control for heterogeneity in the diffusion pattern of charging stations.

All OLS regressions find a positive and statistically significant coefficient for the installed EV base. The estimate results in Column (d) suggest that a 10% increase in the EV fleet size would lead to a 1.2% increase in the number of public charging stations. The GMM results in column (e) show that a 10% increase in EV fleet size would result in a 6.1% increase in charging stations. In Column (f), we add the EV incentives (tax credits and rebates at the federal and state levels)

[25]EV models only represent less than 0.8% of new vehicle sales in the nation in 2013. Including models of other fuel types would not help us identify the indirect network effects since their demand does not depend on EV charging stations. We believe that micro-level data with the second-choice information is much better suited to assess the substitution pattern between EVs and different types of non-EVs than the aggregate data that we currently have. This is an ongoing work of the authors.

as an additional instrument and the coefficient for charging stations increases from 0.613 to 0.659. We take Column (e) as our baseline IV specification due to the concern that the EV incentives (especially those at the state level) could be endogenous as they could be a response to the unobserved shocks to the deployment of charging stations.

The GMM coefficient estimates are higher than all the OLS estimates, suggesting that the installed base of EVs is negatively related to the unobserved shocks to charging station investment, leading to downward bias in OLS. An example of the unobserved shocks is the unobserved local policies: policy makers may design policies to support charging station investment to counteract negative EV demand shocks.

The results in Column (e) show that tax credits and the availability of public funding for charging stations have positive but statistically insignificant coefficients. The tax credits and public funding are both at the state level. The dependent variable in the charging station equation, however, only includes publicly-accessible charging stations, which are mainly subsidized by the federal government directly through the federal projects such as the EV Project and ChargePoint Project. Although state-level tax credits and funding also apply to public charging stations, they mostly support the installation of charging stations at workplace and multi-family dwellings, which are usually privately-accessible and are excluded from our analysis. The interaction term of grocery stores with the lagged number of stations in all MSAs other than own has a positive and statistically significant coefficient, consistent with our argument for using it as a relevant instrument in the EV demand equation.

1.6 Policy Simulations

Our empirical analysis suggests that indirect network effects exist on both sides of the market. In this section, we first examine the policy impact of the current federal income tax credit policy for EV buyers and then compare this policy with an alternative policy that subsidizes charging station investment instead.

1.6.1 Impact of Income Tax Credits

The federal government has adopted several policies to support the EV industry including providing federal income tax credits for EV purchase, R&D support for battery development, and funding for expanding charging infrastructure. The Congressional Budget Office (CBO) [21] estimates that the total budgetary cost for those policies will be about $7.5 billion through 2017. The tax credits for EV buyers account for about one-fourth of the budgetary cost and are likely to have the greatest impact on vehicle sales. Under the tax credits policy, EVs purchased in or after 2010 are eligible for a federal income tax credit up to $7,500. Most popular EV models on the market are eligible for the full amount.[26]The credit will expire once 200,000 qualified EVs have been sold by each manufacturer.

In order to examine the effectiveness of the income tax credit policy in terms of stimulating EV sales, we use our parameters estimates from the two baseline GMM regressions to stimulate the counterfactual sales of EVs that would arise

[26]The only EV models that are not eligible for the full amount of credits are Honda Accord Plug-in, Ford C-Max Energi, Porsche Panamera, and Toyota Prius plug-in. And their eligible tax credits are $3,626, $4,007, $4,751.8, and $2,500 respectively. In our policy simulation, we remove the tax credits based on different models.

in the absence of the $924.2 million worth of tax credits to EV buyers from 2011 to 2013. The impact of the policy depends not only on the price elasticity of EV demand in the EV demand equation, but also on the magnitude of indirect network effects captured in both equations.

We assume in our simulations that the MSRPs will not be affected implying that the consumers previously captured all the subsidies. We believe that this is a reasonable assumption in the EV launch stage when automakers produce EVs likely at a loss since the production level is far below the efficient production scale.[27] While more and more states are providing subsidy programs to encourage the adoption of EVs, the retail prices for electric vehicles have actually been decreasing (for the same model) during our sample period likely due to decreasing production cost and the increasing competition.

Our simulation results in Table 1.9 show that EV sales would have been 56,690 less (or 40.44% of the total sales) from 2011 to 2013 without the $924.2 million worth of income tax credit to EV buyers. If we shut down feedback loops, the sales contribution from the tax credit policy would only have been 33,949 (24.2% of the total sales). This implies that feedback loops magnify the policy shock and explain 40% of the sales increase from the policy. The results suggest feedback loops have a multiplier effect of 1.67. CBO finds the policy impact to be 30% of the total EV sales while their study only considers the price effect of the tax credit but not the role of indirect network effects in amplifying the policy effect [21]. DeShazo et al. (2014) [29] study the California Clean Vehicle Rebate Projects for EVs and find a 7% increase in EV sales from the rebate of

[27]In a study by Sallee (2011) on the income tax credit on hybrid vehicles after hybrid vehicles were first introduced to the market, he finds consumers captured the majority of the gains for the income tax subsidy. Automobile assembly lines generally operate most efficiently with an output of 200,000 to 250,000 vehicles per platform [86]. The global sales of the most popular EV model, Nissan Leaf, was only 61,027 in 2014.

$1,838 on average. Neither of these studies takes into account indirect network effects and their estimates likely provide the lower bounds of subsidy impacts.

1.6.2 Policy Comparison

Our stylized model suggests that feedback loops from indirect network effects on both sides of the market have important policy implications. A policy shock on one side of the market would affect the other side. To promote EV adoption based on a variety of rationale as discussed in Section 1.2.2, policy makers face a problem of optimal policy design in that the tax revenue can be used to subsidize one or both sides of the market. We compare the subsidy policy on EV purchase with an alternative policy of subsidizing charging station investment. The alternative policy uses the same budget of $924.2 million evenly in each quarter during 2011-2013 to install charging stations in all MSAs (proportional to population). As a lower bound estimate of the investment cost of charging stations, we assume the government is only responsible for the purchase and installation of the charging hardware and the charging station company will then operate and maintain the charging stations, as in the case of the EV Project and ChargePoint Project, the two federal charging station support programs. As a robustness check, we also estimate an upper bound investment cost for charging stations assuming the government will also need to maintain and operate those charging stations. The lower bound and the upper bound of the charging station investment cost are $27,000 and $50,244 respectively. [28]

[28]According to the charging station cost report by U.S. Department of Energy Vehicle Technologies Office (2015), the maintenance and operation cost of charging stations include the following components: electricity use, network fee, maintenance and repair, and rents in parking lots. The average electricity consumption is reported to be 6,864 kWh per year with an average network fee of $500 and maintenance fee of $300. Assuming the charging station charges cus-

The policy comparison between these two policies is provided in Table 1.10. We assume the policy period from 2011 to 2013 (i.e., no subsidy available in either policy after that). The existing tax credit policy (policy 1) has led to 56,690 more EVs from 2011 to 2013, amounting to $16,303 for one additional EV. The policy effect will continue to exist until the feedback loops die out in 2055. [29] The impact on EV sales from this policy in the long term would be 184,049, amounting to $5,022 per policy-induced EV purchase. If instead, the government had spent the $924.2 million subsidizing charging stations by purchasing and installing charging infrastructure (policy 2 with lower station cost), EV sales would have increased by 124,904 during these three years. The cumulative impact on EV sales from this policy until year 2055 would be 403,558, amounting to $2,290 per induced EV, only 46% of the unit cost under the existing policy. If the government were also responsible for maintaining and operating those stations (policy 2 with higher station cost), EV sales would have increased by 75,199 during these three years and 267,741 in the long term, amounting to $3,452 per induced EV, still preferable to policy 1.

As depicted in Figure 1.6, policy 2 that subsidizes charging station investment demonstrates a dominant advantage in stimulating EV sales in the early stage of the EV market. The $924.2 million spending during the three years can install about 18,395 to 34,231 charging stations depending on the actual investment cost. This is more than one eighth to one fourth of the total number

tomers $0.39 per kWh (the current charging fee of Blink Network supported by the EV project) and the average annual parking lot rate being $ 1995.12 (the national average parking lot rate in 2012 Colliers International Parking Rate Survey), the estimated operation and maintenance cost less revenue is $805 per charging unit and $2,896 per station (3.6 units per station). Assuming a 10-year life span of a charging station, the discounted total cost of maintenance and operation is $23,244 per station and the total investment cost of a charging station including initial installation is $ 50,244.

[29] We assume the public charging stations and the installed base of EV drivers keep increasing at a rate that was observed in the last quarter of 2013.

of gasoline stations in the country and almost one and half to three times of the current total number of public charging stations in the whole country. This large amount of public charging stations should dramatically alleviate or even eliminate range anxiety for potential EV buyers. Our results indicate that building charging stations is a more effective way to boost EV sales in the EV launch stage. As shown in our regression results, indirect network effects on the EV demand side are much stronger than those on the charging station side (coefficient ratio being 1.4) and consumers are not very sensitive to prices (price elasticity being -1.3). As a result, the policy that builds charging stations stimulates EV sales at a much faster pace, consistent with our findings in the model section.

The long-run simulations are based on a variety of assumptions and are meant to be illustrative. As the technology improves, the EV driving range is likely to increase, weakening indirect network effects from charging stations to EV demand. In addition, in the longer term, as EVs become more of a serious choice for average vehicle buyers, consumer price sensitivity among EV buyers could increase. Both of these changes would affect the policy outcomes and weaken the effectiveness of policy 2 relative to policy 1.

As discussed in Section 1.5.2, the network size of charging stations has heterogeneous impacts on the EV demand across locations with different average commute time. This implies heterogeneity in the relative strength of indirect network effects on the two sides of the EV market and hence heterogenety in policy comparison. That is, policy 2 may not be always preferred as previous analysis suggests. In MSAs where indirect network effects on EV demand are not strong since drivers have shorter commute and home charging is enough to ensure their daily trips, policy 1 that subsidies EV purchase could be more effective. Figure 1.7 depicts the relative effectiveness of the two policies in promoting EV adoption. The MSA with policy 2 being most effective is New York-New Jersey-Long Island (NY-NJ-PA) where the average commute time is longest, while the MSA with policy 1 being most effective is Grand Forks (ND-MN) where the average commute time is shortest. This suggests that a more elaborate and cost-effective policy design would be to subsidize charging stations in areas with long commute (e.g., large MSAs) but to subsidize EV purchases in areas with short commute (e.g., small MSAs). This type of regionally differentiated policy could be implemented at the federal level but perhaps more feasibly at the state and local levels. For example, in states or cities where average commute is longer, state and local government should focus on building charging station infrastructure while subsidies on EV adoption for example through rebate and HOV lane usage can be implemented in states and cities where average commute is shorter.

1.7 Conclusion

This study first demonstrates through a stylized model that positive indirect network effects in both EV demand and charging station deployment give rise to feedback loops which amplify shocks to the system and have important policy implications. Although indirect network effects on both sides of the market imply subsidizing either side of the market will result in an increase in both EV sales and charging stations, the relative cost-effectiveness of different subsidy policies depends on consumer price sensitivity for EVs and the relative magnitude of indirect network effects on the two sides of the market.

The paper provides to our knowledge the first empirical analysis of indirect network effects in this market and evaluates the impacts of the current federal income tax credit program for EV buyers. Our analysis estimates the elasticity of EV adoption with respect to charging station availability to be 0.84 and the elasticity of charging station investment with respect to the EV installed base to be 0.61. These indirect network effects enhance the effectiveness of the tax credit policy, which has contributed to 40% of the EV sales during 2011 to 2013 and will continue to exhibit a positive effect on the market for many years through feedback loops. Given the relatively strength of indirect network effects on the EV demand side and the low price sensitivity of early adopters, subsidizing charging station deployment would be much more cost-effective than the current policy of subsidizing EV purchases.

Our findings offer some insights for policy design to promote the EV technology. First, the policy to expand the charging station network (e.g., through subsidies) would be especially effective in the EV launch stage due to low price-sensitivity of early adopters and strong indirect network effects from charging stations on EV demand. Second, our analysis demonstrates that significant spatial differences exist in optimal policy design. Together with the finding from the literature that the environmental benefits from EVs exhibit significant heterogeneity across locations with different fuel mix of electricity generation, the spatial variation in indirect network effects limits one-size-fit-all policies and argues for regionally differentiated policies.

Table 1.1: Summary Statistics

Variable	Mean	Std.dev
Panel (a): Vehicle Demand Equation		
Sales of a EV model	9.62	40.01
Gasoline prices ($)	3.52	0.26
EV retail price - tax incentives ($)	33161	18569
No. of charging stations	22.13	45.74
Residential charging stations from the EV project	9.21	65.41
Annual personal income ($)	41607	82536
Hybrid vehicle sales in 2007	945	1859
No. of grocery stores	278	624
Average commute (minutes)	22.96	3.37
College graduate share	0.40	0.07
Use public transport to work share	0.02	0.03
Drive-to-work share	0.88	0.05
Share of white residents	0.78	0.11
Number of observations	14563	
Panel (b): Charging Station Equation		
No. of charging stations	9.94	28.13
No. of EV installed base	134	584
Charging station tax credit (%)	4.56	14.7
Public funding or grants	0.33	0.47
No. of grocery stores	186	455
Hybrid vehicle sales in 2007	568	1354
Current gasoline prices ($)	3.49	0.27
Gasoline price last year ($)	3.25	0.39
Gasoline price two years ago ($)	2.78	0.59
Gasoline price three years ago ($)	2.78	0.58
State EV incentives (rebates+tax credits) ($)	1575	3121
Number of observations	4236	

Table 1.2: Parameters for Simulating Indirect Network Effects

Coefficients	Values	Variables	Values
β_1	0.8	p	30,000
β_2	-1.5	X	16
β_3	1	Z	2
γ_1	0.4		
γ_2	1		
δ	0.9		

Table 1.3: EV Demand Equation

Variable	OLS (a)	OLS (b)	OLS (c)	OLS (d)	OLS (e)	GMM (f)
ln(No. of charging stations)	0.378***	0.389***	0.502***	0.352***	0.177***	0.844***
	(0.017)	(0.017)	(0.021)	(0.037)	(0.036)	(0.162)
ln(gasoline price)*PHEV	1.095***	1.186***	1.922***	0.095	-0.033	-0.083
	(0.203)	(0.301)	(0.353)	(0.208)	(0.201)	(0.206)
ln(gasoline price)*BEV	0.611***	0.704***	1.908***	0.560**	0.386*	0.419*
	(0.203)	(0.300)	(0.406)	(0.229)	(0.217)	(0.220)
ln(retail price - tax incentives)	-0.480***	-0.470***	-0.817***	-1.378***	-1.433***	-1.288***
	(0.034)	(0.034)	(0.179)	(0.142)	(0.140)	(0.131)
ln(residential charging from EV project)	0.046*	0.035	0.019	0.026**	0.059***	0.050***
	(0.025)	(0.024)	(0.022)	(0.012)	(0.011)	(0.010)
ln(personal income)	0.667***	0.664***	0.729***	2.018**	1.215*	2.056**
	(0.162)	(0.161)	(0.179)	(0.852)	(0.695)	(0.855)
ln(hybrid vehicle sales in 2007)*time trend					0.031***	0.011**
					(0.003)	(0.005)
ln(personal income)*time trend					0.003	0.001
					(0.016)	(0.020)
Year-quarter fixed effects	No	Yes	Yes	Yes	Yes	Yes
Vehicle model fixed effects	No	No	Yes	Yes	Yes	Yes
MSA-model fixed effects	No	No	No	Yes	Yes	Yes

Table 1.4: First Stage Results for EV Demand Equation

Variable	
ln(No. of grocery stores)*ln(lagged national stations)	0.139***
	(0.023)
ln(retail price-tax incentives)	-0.193***
	(0.054)
ln(gasoline price)*PHEV	0.146
	(0.125)
ln(gasoline price)*BEV	0.064
	(0.135)
ln(residential charging from EV project)	-0.011
	(0.010)
ln(personal income)	-0.980
	(1.035)
ln(hybrid vehicle sales in 2007)*time trend	0.010***
	(0.003)
ln(personal income)*time trend	0.018
	(0.022)
R^2	0.677

Note: The dependent variable is ln(No.of stations). The number of observations is 14563. Standard errors are clustered at the MSA level. The model includes year-quarter fixed effects and MSA-model (e.g., Nissan Leaf in San Francisco) fixed effects. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 1.5: Additional Specifications for Vehicle Demand (a)

Variable	GMM (a)	GMM (b)	GMM (c)	GMM (d)	GMM (e)	GMM (f)
ln(No. of charging stations)	-0.282	0.785***	0.817***	0.791***	0.866***	0.851***
	(0.243)	(0.229)	(0.156)	(0.152)	(0.165)	(0.157)
ln(No. of stations)*commute time	0.038***					
	(0.010)					
ln(gasoline price)*PHEV	-0.086	-0.090	-0.079	-0.075	0.037	-0.093
	(0.193)	(0.200)	(0.205)	(0.204)	(0.204)	(0.245)
ln(gasoline price)*BEV	0.389*	0.411*	0.424*	0.440*	0.292	0.440*
	(0.208)	(0.217)	(0.221)	(0.218)	(0.222)	(0.256)
ln(retail price - tax incentives)	-1.324***	-1.294***	-1.214***	-1.300***		-1.499***
	(0.130)	(0.130)	(0.147)	(0.130)		(0.150)
ln(residential charging from EV project)	0.049***	0.048***	0.049***	0.051***	0.054***	0.049***
	(0.009)	(0.012)	(0.010)	(0.009)	(0.009)	(0.010)
ln(personal income)	1.896***	1.710*	2.059**	2.026**	2.167**	2.849***
	(0.708)	(0.958)	(0.868)	(0.839)	(0.859)	(1.040)
ln(hybrid sales in 2007)*time trend	0.011***	0.019	0.011**	0.012**	0.011**	0.009
	(0.004)	(0.024)	(0.005)	(0.005)	(0.005)	(0.006)
ln(personal income)*time trend	-0.001	0.044	0.002	0.003	-0.004	-0.020
	(0.015)	(0.081)	(0.020)	(0.019)	(0.020)	(0.027)
ln(hybrid sales in 2007)*time trend^2		-0.000				
		(0.001)				
ln(personal income)*time trend^2		-0.003				
		(0.005)				
ln(No. of stations)*Battery EV			0.094			
			(0.059)			
College shares*time trend						-0.023
						(0.081)
Drive-to-work share*time trend						-0.117
						(0.116)
Use public transit to work*time trend						0.071
						(0.167)
White share*time trend						-0.100**
						(0.040)

Table 1.6: Additional Specifications for Vehicle Demand (b)

Variable	GMM (g)	GMM (h)	GMM (i)	GMM (j)	GMM (k)
ln(No. of charging stations)	0.842***	0.953***	1.005***	0.725***	0.683***
	(0.162)	(0.170)	(0.281)	(0.224)	(0.347)
ln(gasoline price)*PHEV	-0.083	0.099		0.127	0.176
	(0.206)	(0.211)		(0.204)	(0.201)
ln(gasoline price)*BEV	0.420*	0.590**	0.024	0.238	0.223
	(0.220)	(0.231)	(0.283)	(0.218)	(0.220)
ln(retail price - tax incentives)	-1.288***	-1.283***	-0.927***	-1.297***	-1.307***
	(0.131)	(0.131)	(0.268)	(0.135)	(0.139)
ln(residential charging from EV project)	0.050***	0.049***	0.027	0.054***	0.055***
	(0.009)	(0.011)	(0.020)	(0.012)	(0.011)
ln(personal income)	2.058**	2.184**	0.045	1.764**	2.900***
	(0.854)	(0.933)	(1.362)	(0.831)	(0.835)
ln(hybrid vehicle sales in 2007)*time trend	0.011**	0.006	0.013	0.014**	0.015*
	(0.005)	(0.005)	(0.008)	(0.006)	(0.008)
ln(personal income)*time trend	0.001	-0.001	0.014	0.008	0.007
	(0.020)	(0.020)	(0.032)	(0.020)	(0.020)
Observations	14563	14563	6720	14328	13990

Table 1.7: Charging Station Equation

Variable	OLS (a)	OLS (b)	OLS (c)	OLS(d)	GMM(e)	GMM (f)
ln(EV installed base)	0.374***	0.540***	0.136***	0.115***	0.613***	0.659***
	(0.025)	(0.028)	(0.029)	(0.028)	(0.157)	(0.157)
Charging station tax credit (%)	-0.005***	-0.003*	0.003	0.003	0.012	0.012
	(0.002)	(0.002)	(0.013)	(0.014)	(0.014)	(0.014)
Public funding or grants	0.099*	0.077	0.007	-0.020	0.078	0.088
	(0.060)	(0.057)	(0.048)	(0.047)	(0.054)	(0.055)
ln(No. of grocery stores)*ln(lagged national stations)	0.042***	0.030***	0.183***	0.118***	0.063**	0.058**
	(0.005)	(0.005)	(0.017)	(0.020)	(0.025)	(0.025)
ln(hybrid vehicle sales in 2007)*time trend				0.018***	0.009**	0.009*
				(0.003)	(0.004)	(0.005)
Year-quarter fixed effects	No	Yes	Yes	Yes	Yes	Yes
MSA fixed effects	No	No	Yes	Yes	Yes	Yes
Overidentification test (p-value)					0.3435	0.1347
Under-identification test(p-value)					0.0000	0.0001

Table 1.8: First Stage Results for Charging Station Equation

Variable	
ln(current gasoline price)	0.206
	(0.233)
ln(gasoline price last year)	3.304***
	(0.824)
ln(gasoline price two years ago)	3.236***
	(0.676)
ln(gasoline price three year ago)	3.087***
	(0.810)
ln(hybrid vehicle sales in 2007)*time trend	0.021***
	(0.004)
ln(No. of grocery stores)*ln(national charging stations)	0.085***
	(0.023)
Charging station tax credit (%)	-0.017
	(0.018)
Public funding or grants for stations	-0.228***
	(0.061)
R^2	0.922

Note: The number of observations is 4236. The dependent variable is ln(EV stock). The model includes year-quarter fixed effects and MSA fixed effects. Standard errors are clustered at the MSA level. *Significant at 10%, **significant at 5%, ***significant at 1%.

Table 1.9: Policy Impacts of Federal Income Tax Credits for EVs

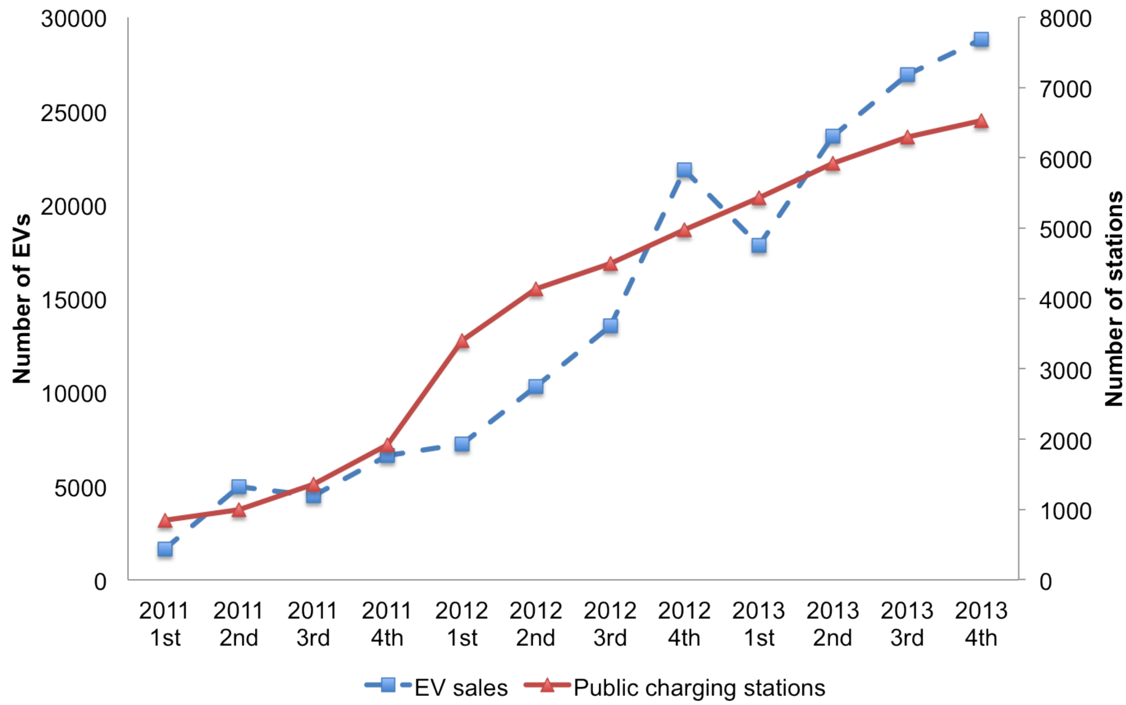
Time	Observed EV Sales	Counterfactual Sales	Sales Reduction	Percentage
2011-1	1,105	772	333	30.10%
2011-2	3,241	2,580	661	20.40%
2011-3	2,813	1,887	926	32.91%
2011-4	3,900	2,256	1,644	42.16%
2012-1	4,307	2,015	2,292	53.22%
2012-2	7,030	3,517	3,513	49.97%
2012-3	9,662	5,575	4,087	42.30%
2012-4	12,665	7,838	4,827	38.11%
2013-1	21,140	12,931	8,209	38.83%
2013-2	24,803	15,571	9,232	37.22%
2013-3	25,782	15,679	10,103	39.19%
2013-4	23,747	12,884	10,863	45.74%
Total	140,195	83,505	56,690	40.44%

Note: Counterfactual sales are the simulated sales in all 353 MSAs in our data after removing the federal income tax credit for EV buyers (the amount based on different models) while holding everything else the same.

Table 1.10: Comparison of EV Income Tax Credit and Charging Station Subsidy Policies

	EV Sales Increase from Policy 1	EV Sales Increase from Policy 2 Low Cost	EV Sales Increase from Policy 2 High Cost
2011-1	333	2,532	1,439
2011-2	661	3,839	2,214
2011-3	926	4,116	2,422
2011-4	1,644	5,937	3,505
2012-1	2,292	6,500	3,891
2012-2	3,513	8,599	5,185
2012-3	4,087	9,074	5,482
2012-4	4,827	9,856	5,966
2013-1	8,209	17,832	10,762
2013-2	9,232	18,340	11,088
2013-3	10,103	18,880	11,443
2013-4	10,863	19,397	11,801
Sales increase in 3 years	56,690	124,904	75,199
Total increase long-term	184,049	403,558	267,741
Total increase in 10 years	168,131	373,748	245,687
Government spending per EV	$5,022	$2,290	$ 3,452

Figure 1.1: National Quarterly EV Sales and Public Charging Stations

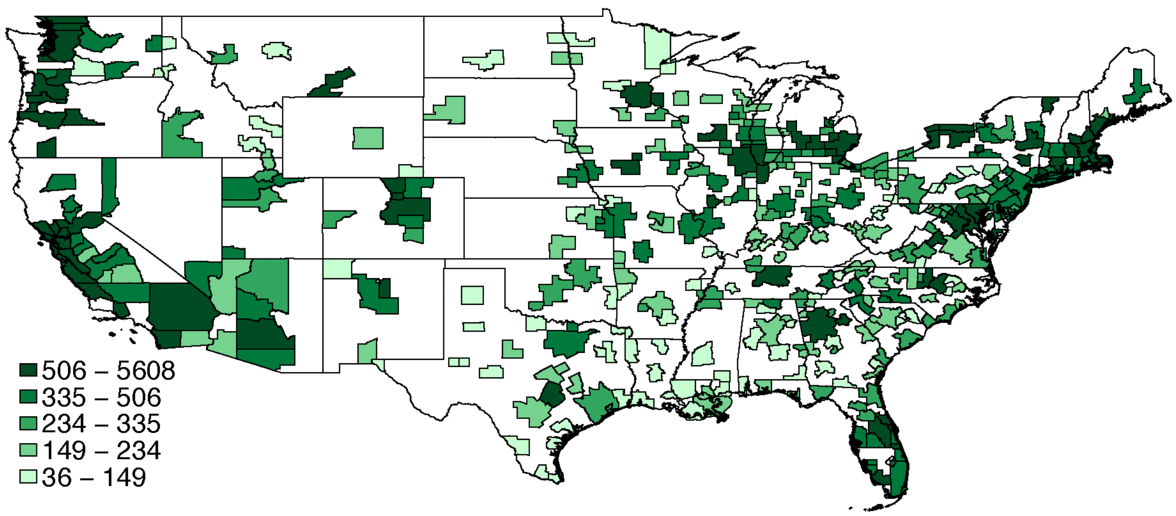


Source: Author's calculations using Hybridcars.com monthly sales dashboard data and electric charging station location data by Alternative Fuel Data Center of the Department of Energy.

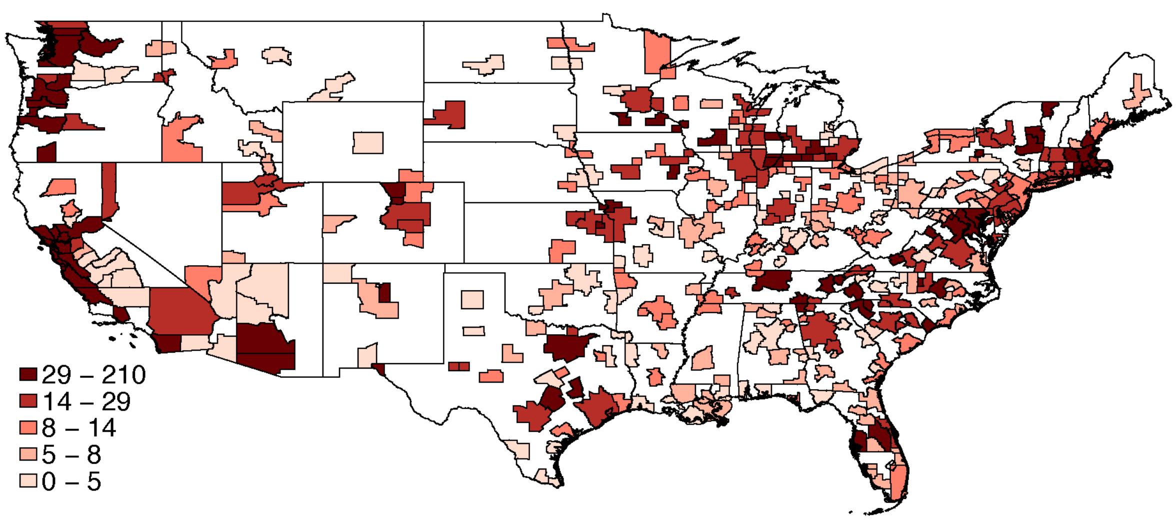
Note: The quarterly EV sales plotted include both BEV and PHEV sales.

Figure 1.2: Spatial Distribution of EVs and Public Charging Stations

Panel (a) Installed Base of EVs Per Million People

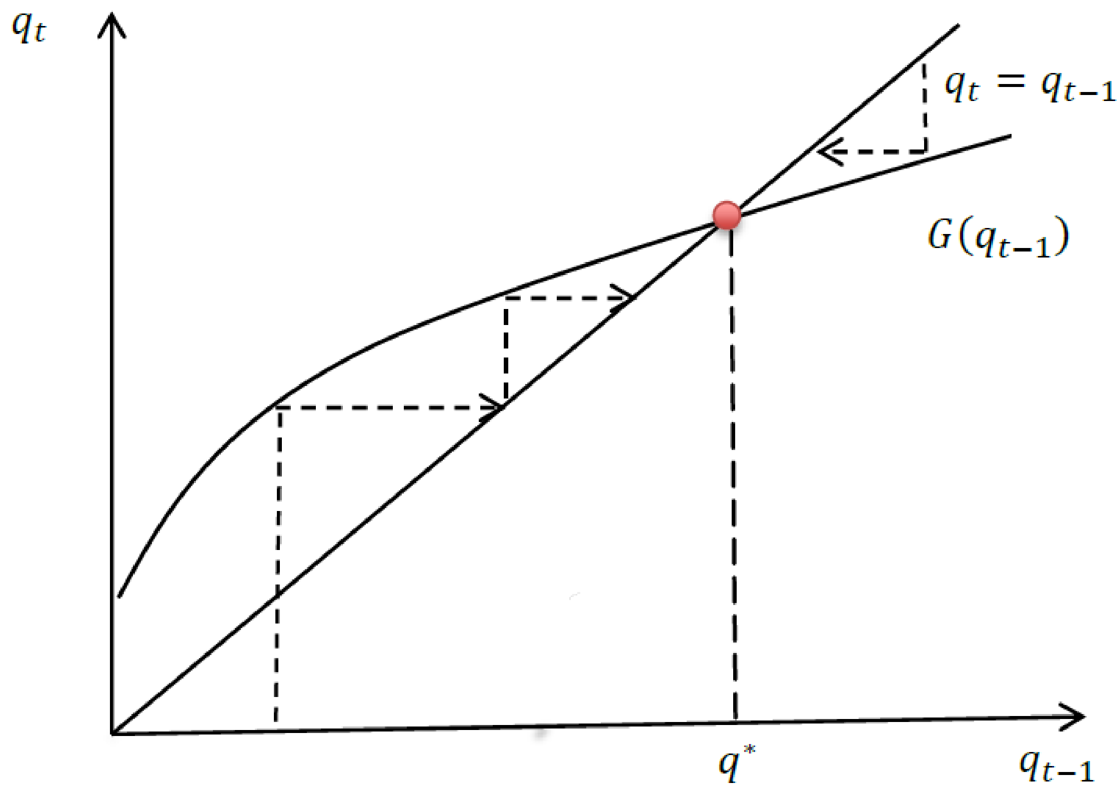


Panel (b) Public Charging Stations Per Million People



Note: Map boundaries define metropolitan statistical areas. Both graphs are shown for the fourth quarter of 2013).

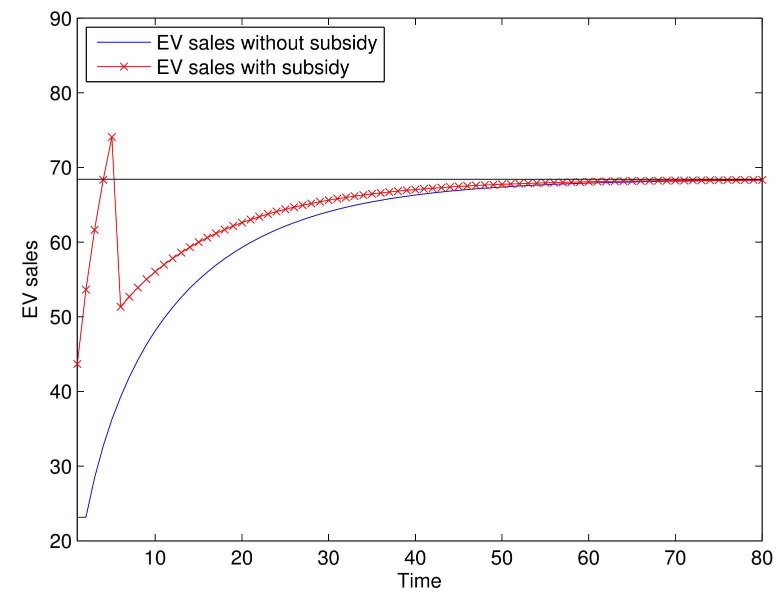
Figure 1.3: Steady State Solution and Stability



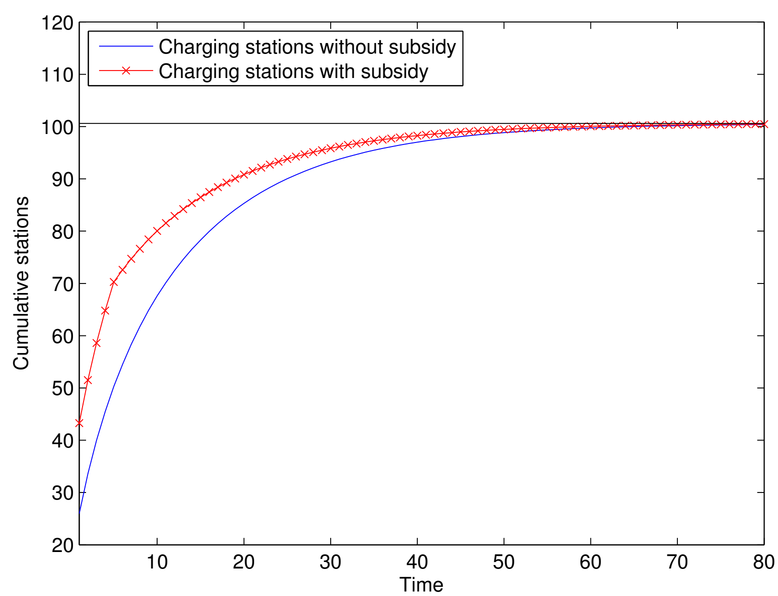
Note: q_t is the number of new EV sales in each period. $q_t = G(q_{t-1})$ is the implicit function defined in equation (1.3). $q*$ is the steady state solution.

Figure 1.4: Impacts of Income Tax Credits (5 periods) under Feedback Loops

Panel (a) EV Sales Increase Due to Feedback Loops

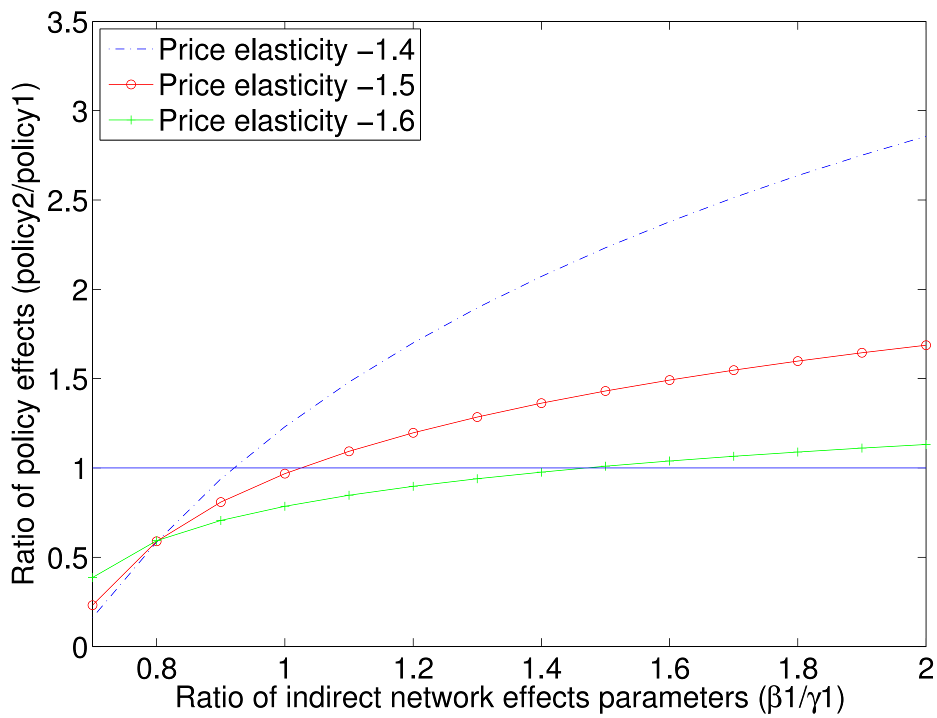


Panel (b) Charging Stations Increase Due to Feedback Loops



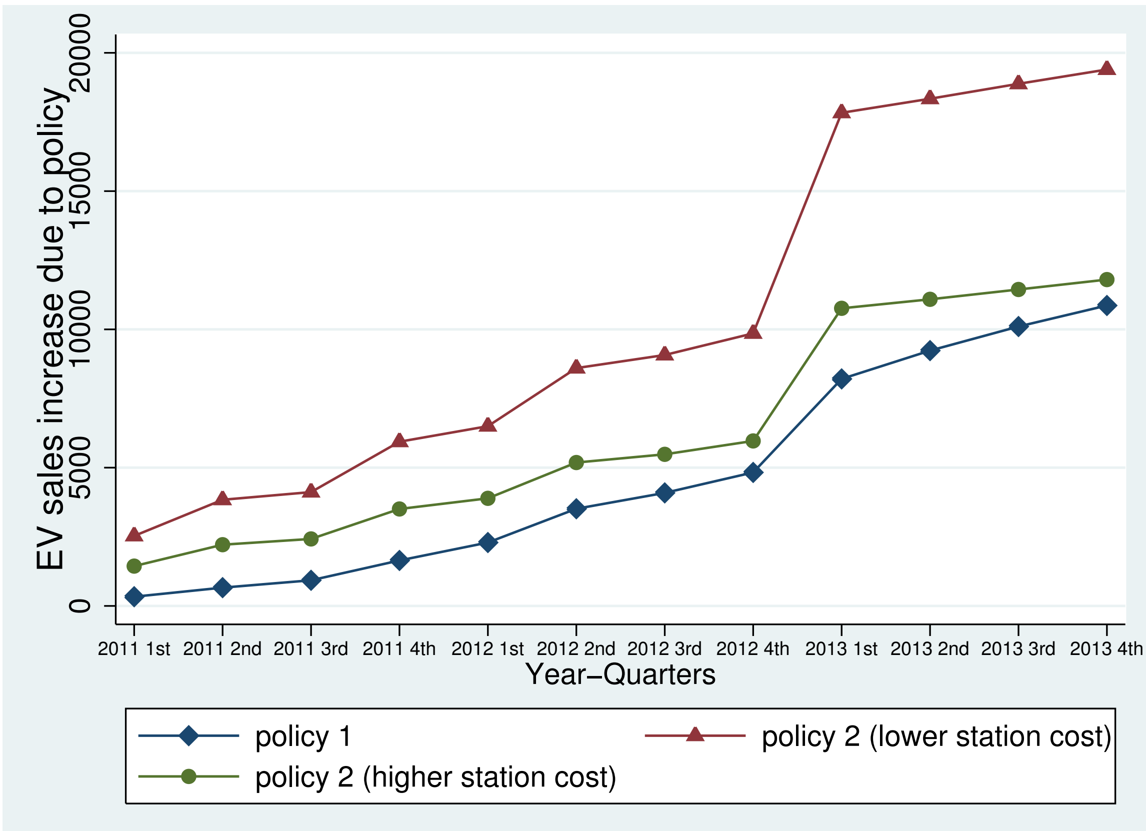
Note: The simulated subsidy effects are due to a policy design that gives EV buyers a tax credit of $7,500 for the first five periods.

Figure 1.5: Policy Comparison and Relative Strengthen of Indirect Network Effects



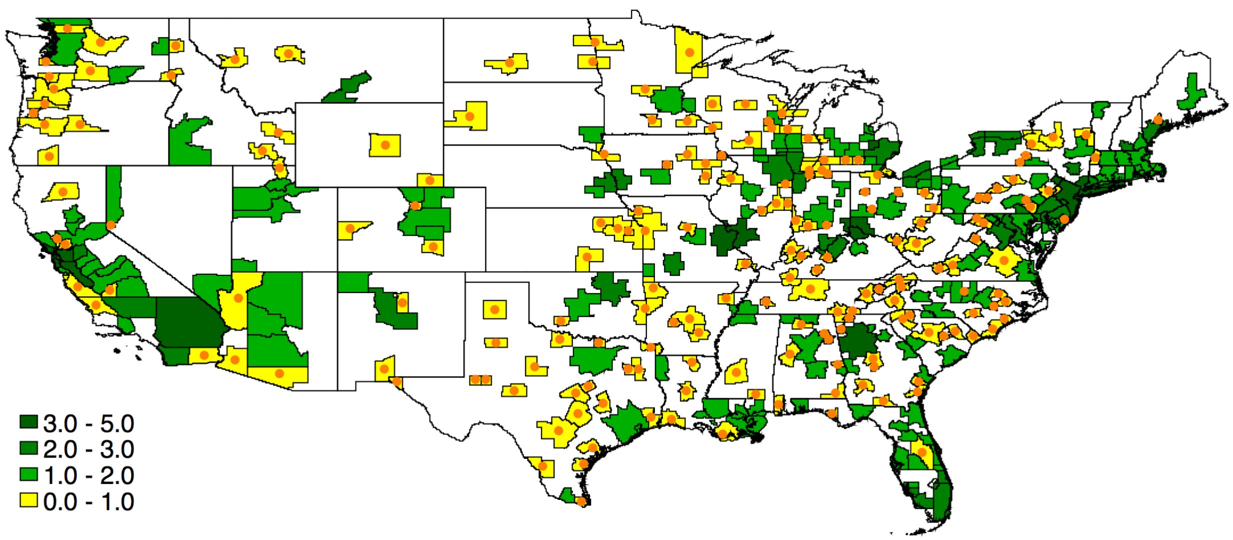
Note: This figure depicts the relationship between the relative policy effects of two subsidy designs and the relative strengthen of the indirect network effects on both sides of the EV market. Policy 1 subsides the EV purchase by tax credits and policy 2 uses the same amount of funding subsidizing charging stations. Given a price elasticity of EVs, Policy 2 becomes more and more effective than Policy 1 when the effect of charging stations on EV demand (denoted by β_1) becomes larger relative to the effect of EV stock on charging stations (denoted by γ_1). When the magnitude of the price elasticity increases (decreases) and consumers are more (less) sensitive to prices, policy 2 becomes less (more) effective relative to policy 1 for a given ratio of β_1 / γ_1.

Figure 1.6: Sales Impacts from Two Subsidy Policies



Note: Each data point represents EV sales increase by quarter due to the policy. Policy 1 gives new EV buyers a tax credit of $2,500-$7,500 based on different models as the current income tax credit policy for EVs. Policy 2 builds charging stations in all MSAs with the same total spending as policy 1 by assuming a charging station investment cost with a lower bound cost of $27,000 and an upper bound of $50,244.

Figure 1.7: Heterogeneous Policy Effectiveness (Policy2/Policy1)



Note: Policy 1 gives new EV buyers a tax credit of of $2,500-$7,500 based on different models as the current income tax credit policy for EVs. Policy 2 builds charging stations in all MSAs with the same budgetary cost as policy 1 assuming the investment cost per station being $27,000. The figure plots the ratio of the EV increases due to the two subsidy policies. The policy effectiveness of policy 2 varies across locations due to the heterogeneous impacts of public charging stations on the EV demand. The regions with the dots are locations where policy 1 is more effective.

CHAPTER 2

THE SUBSTITUTION PATTERN OF ELECTRIC VEHICLES

2.1 Introduction

The electrification of the transportation sector through the diffusion of plug-in electric vehicles (EVs), coupled with cleaner electricity generation, is considered a promising pathway to reduce air pollution from on-road vehicles and to strengthen energy security. Different from conventional gasoline vehicles with internal combustion engines, EVs use electricity stored in rechargeable batteries to power the motor and the electricity comes from external power sources. When operated in all-electric mode, EVs consume no gasoline and produce zero tailpipe emissions. But emissions shift from on-road vehicles to electricity generation, which uses domestic fuel source. The environmental benefits of promoting EVs critically depend on the fuel source of electricity generation [48] and also what types of cars do the policy-induced EV replace. The environmental implication of replacing a gasoline vehicle with lower fuel efficiency would be different from replacing a hybrid vehicle (HEV) with higher fuel economy.

Since the introduction of the mass-market models into the U.S. in late 2010, monthly sales of EVs have increased from 345 in December 2010 to 13,388 in December 2015.[1] Despite the rapid growth, the market share of electric cars is still small: the total EV sales only made up 0.82% of the new vehicle market in 2015 (Figure 2.1). To overcome the barriers to wider adoption of EVs such as high purchase cost, limited driving range, the lack of charging infrastruc-

[1]From 1996 to 1998, GM introduced over 1000 first-generation EVs (EV1) in California, mostly made available through leases. In 2003, GM crushed their EVs upon the expiration of the leases.

ture and long charging time, both the federal and state governments provide different forms of incentives. The federal government provides federal income tax credit to new qualified EVs based on each vehicle's battery capacity and the gross vehicle weight rating, with the amount ranging from $2,500 to $7,500. Several states have established additional state-level incentives to further promote EV adoption such as tax exemptions and rebates for EVs and non-monetary incentives such as HOV lane access, toll reduction and free parking. In addition, federal, state and local governments provide funding to support charging station deployment. For example, the Department of Energy provided ECOtality Inc. $115 million grant to build residential and public charging stations in 22 U.S. cities in collaboration with local project partners.

A potential problem associated with the direct subsidy to consumers is that the policy may not lead to "additionality" in the sense that many of the EV buyers may still purchase EVs even if there were no subsidy. Since early adopters of EVs are those who favor the newest technology and who have the strongest environmental awareness and usually have higher income, [2] it is more likely that the effect of a uniform subsidy policy such as the current federal income tax credit policy in terms of boosting additional EV sales is limited. California Clean Vehicle Rebate Program (CVRP) used to offer incentives of $1,500 to PHEVs and $2,500 to BEVs, but the majority of the rebates went to households with higher-income. In order to direct the rebates towards households who value the rebates most, CVRP has been redesigned such that lower-income households will be able to claim more generous rebates. The households with income less that 300 percent of Federal Poverty Limit will be able to get $3,000

[2] According to California Plug-in Electric Vehicle Owner Survey (2014), among buyers of conventional new vehicles, 15% of households have annual household income over $150,000 while that share is 54% among EV buyers.

for PHEVs and $4,000 for BEVs, and the households with gross annul income above certain thresholds are no longer eligible for the rebates: $250,000 for single filers, $340,000 for head-of-household filers and $500,000 for joint filers.

Moreover, even if the tax credits make additional EV purchases by making potential consumers to switch from other fuel types to EVs, the policy effects in terms of environmental benefits may still not be additional if they replace vehicles with fuel efficiency that is already high. First, the emission reduction of additional EVs depend largely on the emission from generating the electricity that is used to fuel EVs, which varies significantly across locations. In some locations where electricity comes mainly from coal-fired generation, EVs even generate negative environmental benefits if they replace their gasoline counterparts [48]. Second, the emission reduction from additional EVs also depend on which vehicles were replaced by EVs, or the fuel economy of the forgone vehicles when consumers purchase EVs. The lower the difference in emissions between EVs and the vehicles that consumers would have purchased without the subsidy, the lower the emission reduction. The substitution pattern between EVs and other fuel types is thus critical when evaluating the environmental benefits of promoting EVs.

Taking advantage of a survey data set of U.S. new vehicle buyers from 2010 to 2014 which are rich in consumer demographic variables and a national level automobile registration data set with vehicle model and fuel type breakdowns, this study is able to estimate a demand model of U.S new automobile market and investigate the substitution pattern of EV models, which could provide insight of the environmental implications of different EV models and guidance of implementing more effective subsidy programs. With the estimated parameters for consumer preference, this study is also going to simulate counterfactual market outcomes when removing the EVs from the market or removing the federal EV subsidy to examine the substitution pattern of the EV market and the cost-effectiveness of the federal income tax credits policy in terms of reducing emissions from the vehicle fleet. When evaluating the environmental benefits of EVs, Holland et al. (2016) [48] assigned each electric vehicle a substitute gasoline vehicle that captures the closest substitution in terms of non-price attributes. As a robustness check, they also rely on the survey data where consumers report alternative vehicle choices to form the substitute gasoline vehicles. However, this approach assumes that all sales of a specific EV model replaces the same substitute gasoline vehicle, which is often not the case in reality. For example, due to consumer heterogenous preferences, some Nissan Leafs replace Toyota Prius, and other Nissan Leafs might replace Ford Fusion. In addition, this approach requires having a representative sample of consumers who report second choices for each EV model, which might not be available in some cases. [3] Unlike using survey data solely to assign a substitute model for each EV, we estimate a vehicle demand model incorporating both aggregate sales data and micro-level survey data. The estimated own- and cross-price elasticities can directly reflect the substitution pattern between EVs and vehicles of other fuel types. The recovered consumer preference parameters can also help us conduct simulations to directly quantify the emission difference between the observed EV sales and the simulated replaced vehicles, and also the impact of the subsidy programs in boosting EV sales.

This study directly contributes to the following three strands of literature.

[3]Holland et al. (2016) [48] use create a composite substitute gasoline vehicle for each EV by taking the weighted average of emissions of the top gasoline substitute vehicles reported in the survey. But they do not have substitute choice data for certain EV models including Honda Fit EV, Fiat 500 EV, and BYD e6.

First, our study adds to the emerging literature on the market of electric vehicles. Congressional Budget Office (2012) [21] estimates the effect of income tax credits for EV buyers based on previous research on the effects of similar tax credits on conventional hybrid vehicles and finds that the tax credit could contribute to nearly 30% of future EV sales. DeShazo et al. (2014)[29] use a statewide survey of new car buyers in California to estimate price elasticities and willingness to pay for different vehicles and then simulate the effect of different rebate designs. They estimate that the rebate policy in California that offered all income classes the same rebate of $2,500 for BEVs and $1,500 for PHEVs lead to a 7% increase in EV sales. Helveston et al. (2015) [46] model consumer preferences for conventional, hybrid, and electric vehicles in China and U.S. using data from choice-based conjoint surveys and and simulate the market shares of EVs under different subsidy amounts. Their results suggest that BEVs have a larger share in China than in U.S. and the share of low-range PHEVs is higher in U.S. than in China when both of the two countries have comparable subsidies. Their study also finds that older, wealthier and more educated consumers, especially those who own multiple vehicles and have children in households, are less senstive to upfront and operating costs of EVs. Dimitropoulos et al. (2016) [31] evaluates the effects of the favorable tax treatment of electric vehicles in the company car market by using data from a new survey among Dutch company car drivers. They also analyze drivers' sensitivity to changes in applicable tax base rates and other vehicle characteristics and find that drivers are sensitive to changes in tax base rates and there exist substantial heterogeneity in drivers' sensitivity to company car's list prices. Using market-level sales data, Li et al. (2016) [70] offered the first study in quantifying the role of indirect network effects in the EV market and their implications on government subsidies. They find in the EV market which exhibits indirect network effects, indirectly subsidizing charging stations is more effective in increasing EV sales considering early adopters are less price sensitive. Springel (2016) [91] estimates a structural model of consumer vehicle choice and charging station entry in Norwegian EV market and compare the effectiveness of direct purchasing price subsidies with charging stations subsidies. Li (2017) [68] studies the effect of compatibility in U.S. EV market where three incompatible standards for charging stations exist. She shows that mandating compatibility in charging standards would increase the sales of EVs. Our study differs from the earlier work by taking a structural method to estimate the demand of U.S. automobile market with all the vehicle models included and focusing on the substitution pattern between electric vehicles and the vehicles of other fuel types.

Second, our analysis contributes to the rich literature on the diffusion of vehicles with advanced fuel technologies (e.g., hybrid vehicles) and alternative fuels (e.g., FFVs). Kahn (2007) [55], Kahn and Vaughn (2009)[56], and Sexton and Sexton (2014) [89] examine the role of consumer environmental awareness and signaling in the market for conventional hybrid vehicles. Heutel and Muehlegger (2012) [47] study the effect of consumer learning in hybrid vehicle adoption focusing on different diffusion paths of Honda Insight and Toyota Prius. Several recent studies have examined the impacts of government programs both at the federal and state levels in promoting the adoption of hybrid vehicles including Diamond (2009) [30], Beresteanu and Li (2011) [11], Gallagher and Muehlegger (2011) [38] and Sallee (2011) [88]. Diamond (2009) [30] finds that the effects of monetary incentives on consumer adoption are weak, which could result in incentive payments effectively creating a subsidy for the highest income consumers without significantly affecting their purchase decisions. The monetary incentives may be rewarding those who need the incentive the least for a purchase they would have made anyway. Huse (2014) [50] examines the impact of government subsidy in Sweden on consumer adoption of FFVs and the environmental impacts when consumers subsequently choose to use gasoline instead of ethanol due to low gasoline prices. Based on naturalistic driving data, Langer and McRae (2014) [62] show that a larger network of E85 fueling stations would reduce the time cost of fueling and hence increase the adoption of FFVs. These previous studies consistently find better environmental awareness, higher gasoline price and more generous incentives are associated with higher adoption of the "green" vehicles. Some also examine the effects of different subsidy formats and find that sales tax waiver and HOV incentives could have more significant impact than income tax credits.

Third, our analysis relates to the literature that studies the cost-effectiveness of energy subsidy programs. Allcott et al. (2015) [1] find that some energy efficiency subsidies are poorly-targeted and are primarily taken up by consumers who are wealthier and more informed about energy costs. They conclude that restricting subsidy eligibility could increase the welfare gains from those subsidies. Boomhower and Davis (2014) [19] find that half of all participants would have adopted the energy-efficient technology even with no subsidy. Ito (2015) [51] finds that most of the treatment effects of incentives come from consumers who are closer to the target level of consumption, and that the treatment effect is not significantly different from zero for consumers who are far from the target level. Fowlie et al. (2015) [37] find evidence that high non-monetary costs contribute to the low participation of energy efficiency investment for households and there are demographic differences between households who chose to participate by themselves and who were encouraged to participate in the program by encouragement intervention. By empirically estimating the vehicle demand model and recover consumer preference parameters, we are able to run conter-factual analysis to examine the welfare impact of current subsidy design and quantify to what extent does the subsidy increase the sales of EVs.

Section 2.2 briefly describes the industry and policy background of the study and the data. Section 2.3 presents the empirical model and estimation strategy. Section 2.4 presents the estimation results of the substitution. In section 2.5, we present the counterfactual simulations to evaluate the environmental benefits of the introduction of EVs and the impact of the EV subsidy. Section 2.6 concludes.

2.2 Industry and Policy Background and Data

In this section, we first present industry background focusing on important barriers to EV adoption and then discuss current government policies. Next we present the data used in the empirical analysis.

2.2.1 Industry background

There are currently two types of EVs: battery electric vehicles (BEVs) which run exclusively on high-capacity batteries (e.g., Nissan LEAF), and plug-in hybrid vehicles (PHEVs) which use batteries to power an electric motor and use another fuel (gasoline) to power a combustion engine (e.g., Chevrolet Volt). As depicted in Figure 2.1, monthly EV sales increased from less than 2,000 in the first month of 2011 to nearly 120,000 in December of 2014. Nevertheless, the EV market is still very small: EV sales only made up 0.82% of the total new vehicle sales in the U.S. in 2015.

The diffusion of electric vehicles together with a clean electricity grid can be an effective combination in reducing local air pollution, greenhouse gas emissions and oil dependency. The EV technology is widely considered as representing the future of passenger vehicles. The International Energy Agency projects that by 2050, EVs have the potential to account for 50% of the light duty vehicle sales.[4] Many countries around the world have developed goals to develop the EV market and provide support to promote the diffusion of this technology [74].[5]

EVs are more expensive than their conventional gasoline vehicle counterparts. The manufacturer's suggested retail prices (MSRP) for the 2015 model of Nissan Leaf and Chevrolet Volt are $29,010 and $34,345, respectively, while the average price for a comparable conventional vehicle (e.g., Nissan Sentra, Chevrolet Cruze, Ford Focus and Honda Civic) is between $16,000 and $18,000. To reduce the price gap between EVs and their gasoline counterparts, the Energy Improvement and Extension Act of 2008, and later the American Clean Energy and Security Act of 2009 grant federal income tax credit for new qualified EVs. The minimum credit is $2,500 and the credit may be up to $7,500, based on each vehicle's battery capacity and the gross vehicle weight rating. Moreover, several states have established additional state-level incentives to further promote EV adoption such as tax exemptions and rebates for EVs and non-monetary incentives such as HOV lane access, toll reduction and free parking. California through the Clean Vehicle Rebate Project offers $2,500 rebate to BEV

[4]Hydrogen vehicles (not yet mass-produced) will account for the majority of the remainder. https://www.iea.org/publications/freepublications/publication/EV_PHEV_Roadmap.pdf.

[5]The Chinese government provides rebate of over $9,000 to BEV buyers and nearly $8,000 for PHEV buyers. The UK government offers a grant of up to $7,800 to EV buyers. In Japan, EV buyers were eligible for a subsidy of up to $10,000 in 2013 and $8,500 in 2014.

buyers and \$1,500 rebate to PHEV buyers. In addition, federal, state and local governments provide funding to support charging station deployment. For example, the Department of Energy provided ECOtality Inc. \$115 million grant to build residential and public charging stations in 22 U.S. cities in collaboration with local project partners.

A potential problem associated with the direct subsidy to consumers is that the subsidy may not always result in additional EV sales in the sense that many of the buyers who claim the subsidy may still purchase EVs even if there were no subsidy policy. Since early adopters of EVs are those who favor the newest technology and who have the strongest environmental awareness and usually have higher income, it is more likely that the effect of a uniform subsidy policy, such as the current federal EV income tax credit, on boosting additional EV sales is limited. California Clean Vehicle Rebate Program (CVRP) used to offer incentives of \$1,500 to PHEVs and \$2,500 to BEVs, but the majority of the rebates went to households with high income. In order to direct the rebates towards households who value the rebates most, CVRP has been redesigned such that lower-income households will be able to claim a larger rebate. The households with income less that 300% of Federal Poverty Limit will be able to get \$3,000 for PHEVs and \$4,000 for BEVs, and the households with gross annul income above certain thresholds are no longer eligible for the rebates: \$250,000 for single filers, \$340,000 for head-of-household filers and \$500,000 for joint filers.

Another potential problem with the subsidy is related to the substitution pattern. One of the justifications for EV subsidies is to reduce the emissions from the transportation sector by replacing fuel-inefficient vehicles with EVs. However, when upstream emissions are taken into account, substantial heterogeneity of the environmental benefits could exist. For example, EVs may not have an advantage over conventional vehicles in locations where the electricity is generated through fossil fuels. Thus, even if the EV subsidy results in additional EV purchases, the reduction of overall emissions would be limited. By incorporating spatial heterogeneity of damages and pollution export across jurisdictions, Holland et al. (2016)[49] find considerable heterogeneity in environmental benefits of EV adoption depending on the location and argue for regionally differentiated EV policy. They find the environmental benefits of EVs being the largest in California due to large damages from gasoline vehicles and a relatively clean electric grid and the benefits to be negative in places such as North Dakota where the conditions are reversed.

The fuel economy of the vehicles that get replaced by EVs due to subsidy will determine the effectiveness of the EV subsidy in terms of addressing the environmental externalities. An potential efficiency loss could arise if the subsidy does not induce people to switch from a gas guzzler to an EV but from another fuel-efficient gasoline vehicle to an EV, or another hybrid vehicle to an EV, making little net gain of environmental benefits. Holland et al. (2016) [49]evaluate the heterogenous environmental benefits of EVs by comparing the externalities of EVs with their gasoline counterparts. However, the relative environmental benefits would be smaller if a higher fuel-efficient vehicle such as a hybrid vehicle is compared. At the national average fuel mix, BEVs and PHEVs do not have an advantage over hybrid vehicles in the emission reduction and PHEVs even generate more emissions than hybrid vehicles (Table 2.2). With the expiration of the tax credits for hybrid vehicles, the income tax credits for EVs are very likely to encourage consumers who would otherwise purchase hybrid vehicles to purchase EVs. Table 2.1 shows that as the market share of EVs increase in most recent years, the market share of hybrids started to decline. As the gasoline price increases, the efficacy of the government subsidy for EVs in terms of reducing emissions is further weakened since more consumers would be induced by the market incentive to adopt EVs in the absence of subsidy. Chandra et al. (2010) [22] find that the rebate programs in Canada primarily subsidize people who would have bought hybrid vehicles or fuel-efficient cars in any case and they may not be the most effective way to encourage people to switch away from fuel-inefficient vehicles like large SUVs or luxury sport passenger cars, at least in the short or medium run.

2.2.2 Data

There are three main data sets used to estimate the model of vehicle demand. The first source is the household-level survey data of the Maritz Research U.S. New Vehicle Customer Study, which is a monthly survey of households that purchased or leased new vehicles. The data provides detailed information of demographic characteristics of households who purchased each vehicle, and the alternative vehicles they considered while making the purchase decisions.[6] We use survey data for five model-years: MY 2010 -MY 2014, the first 5 years after the introduction of mass-market EVs, and each model year is defined as September of the previous calendar year to August of the current calendar year (For example, MY 2011 is defined as September 2010-August 2011). For computational purposes, we draw a sample of 11,628 transactions from the cleaned

[6]We only include the most seriously considered models (second choices) in our sample. Many respondents do not report the third and fourth choices. Incorporating the third and fourth choices increase the estimation burden. In order to free up more computation space to include more observations to have more variation in observed consumer characteristics, we did not include the third and fourth choices.

sample after removing observations with missing observed consumer attributes or information on the purchased and seriously considered models, and end up having 1,509, 1,860, 2,287, 2,899, and 3,073 transactions for MY 2010-14 respectively. As the market share of EVs is tiny, in order to include enough EV observations to have enough variation in consumer demographic attributes for EV buyers to identify the different demographic's preference for EVs, we use non-random sampling by including all EV observations from the survey sample and randomly draw observations for the other fuel types. To adjust for non-random sampling, we then follow Manski and Lerman (1977) [73] to include a weighted exogenous sampling maximum likelihood (WESML) by re-weighting the each observation in the likelihood. The weight is defined by the actual market share in the population divided by the within sample market share.

Table 2.3 summarizes the demographic information for the households who made those purchase transactions. The average household income for the survey respondents in the sample is \$140,448, which is larger than the average household income of \$117,795 for married couples in the U.S. considering we over-drew consumers who purchased EVs.[7] The average household size is 2.66 and 63.9% of the heads of household have earned a college degree. 66.1% of the respondents are from an urban or suburban areas with an average commuting of 25.6 minutes and average gasoline price of \$3.48 during the survey time. About 50% of the sampled households selected a light truck and the average price of the vehicles that the sampled households purchased is \$33,451. The average MPG of the purchased vehicles is 34.8.

The survey data is merged with Wards data which provide detailed attributes of each vehicle model for each corresponding model year, including

[7] Data source: IRS Statistics of Income, 2014.

horsepower, size, curb weight, wheelbase, and fuel economy. The data set is further complemented by aggregate vehicle sales data, which provide market-level information of vehicle demand, obtained from registration data complied by IHS Automotive. The IHS data record the quarterly number of registrations for each car model, broken down by fuel type, which are aggregated to model year level to construct the market share for each vehicle model in each model year. All of the above data sets are matched at a model-fuel-type level, for example, Toyota Prius-hybrid. The total number of vehicle models that are defined in the choice set are 424, 404, 417, 441 and 459 respectively for MYs 2010-2014.

We obtain detailed information on locations and open dates of all charging stations from the Alternative Fuel Data Center (AFDC) of the Department of Energy. By matching the ZIP code of each charging station to an MSA and using the station open date, we construct the total number of public charging stations available in each quarter for each MSA. From the American Chamber of Commerce cost-of-living index database, we collect quarterly gasoline prices for each MSA from 2008 to 2013. Household demographics are collected from the American Community Survey.

2.3 Empirical Model and Estimation

In this section, we discuss our empirical model and estimation strategy. We estimate the vehicle demand using random coefficient discrete choice model in the spirit of Berry et al. (1995,2004) [14] [15], Petrin (2002) [81] and Train and Winston (2007) [94].

2.3.1 Vehicle Demand

The consumer characteristics we observe are not representative of the entire population since the consumer-level data we observe is only for people who choose to buy new vehicles during the specific period of time. Therefore, we will estimate the substitution pattern conditioning on buying a new vehicle. Our approach will not be able to capture the substitution between the new vehicle models and the outside option: buying a used car, continuing using their old vehicle, or relying on public transportation. Our estimates will provide the information that what types of vehicles that the policy induced EVs actually replace conditioning on households choosing to purchase a new vehicle. Considering that consumers who purchase EVs are those who are more attentive to environmental impact and the newest technology, the group of consumers who would only purchase EVs with the subsidy but choose not to buy a new vehicle without the subsidy would be small. Therefore, the impact of not modeling the outside option on the evaluation of the subsidy effectiveness is limited.

Household i's utility from purchasing vehicle model j is defined as:

$$u_{ij} = \underbrace{\sum_{k=1}^{K} x_{jk}\bar{\beta}_k - \alpha_1 lnp_j + \xi_j}_{\delta_j} + \underbrace{\alpha_2 \frac{lnp_j}{Y_i} + \sum_{kr} x_{jk} z_{ir} \beta^o_{kr} + \sum_{k} x_{jk} v_{ik} \beta^u_k}_{\mu_{ij}} + \varepsilon_{ij} \tag{2.1}$$

where δ_j is the mean utility of vehicle model j which is constant across consumers in the same market. The x_{jk} stands for the k_{th} vehicle attribute for model j, and we include horsepower, weight, gallons per mile, and some vehicle segment dummy variables as the observed vehicle attributes. The price p_j is the average transaction price observed from the survey data, which is constant for a same model in all locations. The logarithm of price is employed to make the price effect decrease as the price of a vehicle model increases.

The second component μ_{ij} captures heterogeneous utility driven by both observed and unobserved consumer characteristics. Y_i is household i's income in the corresponding year and $1/Y_i$ captures how a household's income influences their price sensitivity. One would expect α_2 to be negative as higher income households would be less sensitive to a price increase due to the diminishing marginal utility of money. z_{ir} denotes consumer i's other demographic variables including family size, education level, whether living in an urban area, the average gasoline price and the number of charging stations in the area, which are interacted with certain vehicle attributes to capture variation in consumer preference due to observed heterogeneity. The unobserved consumer taste v_{ik} is assumed to have a standard normal distribution. The coefficient β_k^u can be interpreted as the standard deviation in the unobserved preference for the vehicle attribute k conditional on the consumer's observed attributes. Let $\theta_1 = \{\beta_{kr}^o, \beta_k^u\}$, denoting the "nonlinear" parameters, and it is understood that the vector $\delta = \{\delta_1, ..., \delta_j\}$ is estimated conditional on a given θ_1. The last component ε_{ij} is the idiosyncratic preference of household i for vehicle model j and it is assumed to have an i.i.d. Type 1 extreme value distribution. The Maritz data includes vehicle models that consumers seriously considered other than the purchased model, which allows for a ranking of both the first and second vehicle choice. Thus, the joint probability of household i choosing j and seriously considering h as an alternative choice when the outside option and j are removed is:

$$P_{ijh} = \int \frac{exp[\delta_j(\theta_1) + \mu_{ij}(\theta_1)]}{1 + \sum_g exp[\delta_g(\theta_1) + \mu_{ig}(\theta_1)]} \cdot \frac{exp[\delta_h(\theta_1) + \mu_{ih}(\theta_1)]}{\sum_{g \neq j} exp[\delta_g(\theta_1) + \mu_{ig}(\theta_1)]} f(v)dv \tag{2.2}$$

The probability of observing household i choosing model j is conditional on the household's v_i vector and the probability is calculated by integrating over the distribution of v. The market demand is the sum of individual consumers' demand and the predicted market share is calculated by calculating P_{ij} with parameters $\theta = \{\beta^o_{kr}, \beta^u_k\}$ and $\delta = \delta_1, ..., \delta_j$ and averaging over the N consumers in the survey sample. We back out the mean utility fixed effects from equating the predicted market shares with the actual market shares from our sales data:

$$S_j = \hat{S}_j(\theta, \delta(\theta, S)) = \sum_n P_{ij}(\theta, \delta(\theta, S))/N \tag{2.3}$$

We include dummy variables for all vehicles models in our sample to estimate consumers' average value of utility from each vehicle. In the numerical search for maximum of the likelihood function, δ is calculated for each trial value of θ. We estimate δ by contraction mapping following Berry et al. (1995):

$$\delta^t_j(\theta, S) = \delta^{t-1}_j(\theta, S) + ln(S_j) - ln(\hat{S}_j(\theta, \delta^{t-1}(\theta, S))) \tag{2.4}$$

We then recover the parameters in mean utility following specification:

$$\delta_j = -\alpha_1 ln p_j + \sum_{k=1}^{K} x_{jk}\bar{\beta}_k + \xi_j$$

where ξ_j denotes the unobserved vehicle attributes of model j. To control for the correlation of price with the unobserved product attributes, following Train and Winston (2007) [94] , we use BLP-style instruments Z_j that measures the sum of distance and squared distance in attribute space between own product and other products in the same firm and from other firms.

2.3.2 Identification

Consumer utility is comprised by three parts: the mean utility portion, the observed heterogeneity component, and the unobserved heterogeneity component. The linear parameters in the mean utility part$\bar{\beta}$ and α_1 are identified through the variation in market shares corresponding to variation in price and other observed vehicle attributes. Due to the potential correlation between price and the unobserved vehicle attributes ξ_j, functions of attributes of other competing products that capture the intensity of competition are used as instruments to provide an exogenous variation in price.

The nonlinear parameters β^o_{kr} and α_2 in the observed individual heterogeneity component are identified with the aid of demographic information observed for different households who purchased different vehicle models. For example, if we observe households with a higher education level disproportionately purchased more electric vehicles, we would expect a positive coefficient for the interaction between household education level and the EV dummy. If higher income groups tend to be less price sensitive to vehicle prices and disproportionately buy more expensive vehicle models, we would expect a negative sign for α_2, which captures the impact of income on consumers' price sensitivity.

The unobserved consumer heterogeneity parameters β_k^u governs the substitution pattern and are mainly identified by the substitution patterns observed from the consumer alternative vehicle choice data. The alternative choices are the choices that consumers make in a choice set where the observed purchased choice is removed. The proximity in the vehicle attributes between the purchased vehicle choice and the alternative vehicle choice facilitates identifying the unobserved heterogeneity parameters β_k^u. For example, if consumers' purchased vehicles and their second choices are often within a certain range for fuel cost, we would expect a statistically significant coefficient for the parameter associated with gallons/mile. Our data sample includes only surveyed households who report both the purchased and alternative vehicle choices, which provides significant identification power in estimating the random coefficients. Berry et al.(2004)[15] note that having micro-level 2^{nd} choice data greatly helps the estimation of random coefficients when they only have observations for one market year and Train and Winston (2007)[94] also mention that including alternative choice data significantly improves the precision of the random coefficient estimates.

2.4 Estimation Results

We first report parameter estimates for the random coefficient model and the use there estimates to calculate price elasticities to show the substitution pattern.

2.4.1 Parameter Estimates

Table 2.4 & 2.5 report the estimation results of the demand model. The mean utility δ represents the average preference consumers have for each vehicle model and are estimated via matching the model predicted market share to the observed market share. The mean preference coefficients for price and each observed vehicle attribute are recovered from IV estimation with the instruments correcting for the endogeneity of price. Both OLS and IV results are reported in Table 2.4 and reflect the preferences for vehicle attributes that are generally expected. In average, consumers have a negative preference for price and the price coefficient in the IV specification is more negative, suggesting OLS underestimates the price sensitivity. Consumers have a positive preference for acceleration, measure by horsepower/weight, and also prefer heavier vehicles. Without interacting with gasoline price, the coefficient for gallons/mile is positive, suggestion average consumers do not like fuel-efficient cars but prefer cars that are more powerful. Consumers in general dislike AFVs and EVs, probably due to limited model choices and unfamiliarity with the new technology. Conditional on other vehicle attributes, consumers do not have a significantly different preference for pickup trucks relative to passenger cars. The positive signs for MY 2011-14 dummies suggest that consumers prefer vehicles in later model years relative to MY 2010, controlling for other vehicle attributes.

Turning to the consumer heterogeneity parameters, with the aid from the individual transaction data, the interaction terms of consumer demographics with vehicle attributes are estimated precisely with intuitive signs. The coefficient of log(price) divided by income captures the extent to which a consumer's price sensitivity varies with income. The negative sign of the estimate suggests that households with lower income react more negatively to a vehicle's price than households with higher income. The elasticities implied from the price preference will be further discussed below. Households of a larger family size prefer larger vehicles that are heavier. Compared with households who live in suburban and rural areas, households who live in urban areas are less likely to adopt pickups, probably due to less towing utility and limited parking space, but are more interested in EVs due to both more frequent city driving needs and better refueling infrastructure provided in urban areas. The interaction of gasoline price with gallons/mile, which measures the operating cost per mile of the vehicle, has a negative sign, suggesting that consumers have a negative preference for the fuel cost. The estimation results also suggest that consumers with better education and live in cities with more charging stations are more likely to adopt EVs.

Four random coefficients are included, which represent unobserved consumer heterogenous preference for gallons/mile, horsepower/weight, light trucks, and AFVs. As indicated by the estimation results, data on consumers' alternative vehicle choices greatly helps precisely identifying those parameters. Based on the standard normal distribution of the random taste v_{ik}, the coefficient β_k^u can be interpreted as the standard deviation in the unobserved preference for the vehicle attribute k. To reduce simulation noise and bias, following [94], we use 150 Halton draws in the simulation of the integral over the unobserved consumer taste v. [8] All of the four coefficients are statistically significant, indicating that consumers have heterogenous preference for those vehicle attributes conditional on the observed consumer characteristics. Those precisely estimated random coefficient parameters help breaking down the I.I.A. problem experienced

[8] Halton draws are a type of low-discrepancy sequence. The demand results are similar when the number of Halton draws are increased to 200.

in traditional logit models and play a critical role in governing the substitution patterns.

2.4.2 Elasticities and Substitution Pattern

The demand system implies sensible elasticities. All implied own-price elasticties are greater than one, ranging from -3.97 to -2.37 with an average being -2.67 and standard deviation being 0.21. The sales-weighted average elasticity among all the 2,146 products in five model years is -2.75. The magnitude of the own-price elasticities are slightly smaller than those obtained in Berry et al.(1995)[14], Petrin (2002) [81], Beresteanu and Li (2011) [11] and Li (2012) [69]. Figure 2.2 plots the own-price elasticities against price and demonstrates that more expensive models tend to have less elastic demand. Table 2.6 demonstrate the cross-price elasticities for a selected group of models. One obvious pattern is that the demand for less expensive models tend to be more price sensitive. More expensive models such as Tesla Model S have lower own-price elasticities in magnitude. Compared with other conventional gasoline vehicles, electric vehicles such as Nissan Leaf and Chevrolet Volt have a larger cross-price elasticity with hybrid vehicles such as Toyota Prius. Battery electric vehicles such as Nissan Leaf and Tesla Model S do not have a large cross-price elasticities with plug-in hybrid vehicles such as Chevrolet Volt. BEVs can only run on electricity and many of them have limited range. PHEVs, on the other hand, rely on gasoline mode to boost the range, since the electric range is only around 30-40 miles. These two different kinds of plug-in vehicles are likely to attract consumers with different driving needs as consumers who have more frequent long-distance travels are more likely to adopt PHEVs. Therefore, it makes sense that no strong substitution exists between PHEVs and BEVs especially when there were only few models during at early deployment stage. Ford F-150, the only pickup truck in the sample, does not have much substitution with the other small and mid-sized sedans and it has almost zero substitution with EV models. The substitution pattern indicates that consumers who purchase EVs generally favor mid-sized sedans that are relatively fuel efficient rather than large vehicles.

Table 2.7 summarizes the elasticity estimates by fuel type. Across different fuel types, the sale-weighted own-price elasticities are similar since all fuel types include vehicle models with a large price range. Each cell in the cross-price elasticity matrix represents the average sales change of a vehicle model of a particular fuel type due to a price change from another vehicle model of other fuel type. For example, a 10% increase in the price of hybrid vehicle model will increase the sales of a BEV model by 0.37% in average, and a 10% increase in the price of another BEV model will increase the sales of a BEV model by 0.13%. Both BEVs and PHEVs have a larger cross-price elasticity with respect to hybrid vehicle models than gasoline, diesel and FFV models, suggesting EV buyers prefer vehicles with better fuel economy. Due to the large selection of model choices, gasoline vehicle is a major substitute fuel type for vehicles of all fuel types. Since our data mostly cover the first few years after the introduction of EVs, the within segment substitution for BEVs and PHEVs is relatively small considering that we do not have enough between-segment variation to identify a strong substitution between EV models.

2.5 Counterfactual Analysis

In this section, we conduct simulations to examine the counterfactual vehicle fleet when all the EV models were removed or when the EV subsidy were removed. The magnitude of the resulting sales changes of the other fuel types could suggest what types of cars were replaced by EVs. The estimated substitution pattern is then translated into emission reduction to assess the environmental benefits of the EV subsidy. The simulation results could provide guidance for future policy designs that intend to better promote alternative fuel technologies.

2.5.1 The Environmental Benefits of EVs

The introduction of EVs could make consumers who would originally choose gasoline vehicles or hybrid vehicles to purchase EVs, and the substitution pattern critically determines the environmental benefits of promoting EVs. To examine the substitution pattern of EVs with other fuel types, we conduct a conterfactual exercise where all EVs are removed from the choice set. The resulting sales changes of other fuel types will reveal what vehicles were replaced by the introduction of EVs. Since we do not allow consumers to choose an outside option as the demand estimation is conditioning on buying a new vehicle, consumers who purchased EVs would switch to another non-EV new vehicle model. In 2014, 109,449 EVs were sold in the U.S. vehicle market. The simulation results suggest that 78.7% of EVs replaced conventional gasoline vehicles, 12% of EVs replaced hybrid vehicles, 2.4% replaced diesel vehicles and the remaining 6.9% replaced flexible fuel vehicles (Table 2.8). The average fuel economy of the vehicles that were replaced by EVs is 28.9 mpg. Among gasoline vehicles replaced by EVs, 74% of them have fuel economy above 25 mpg. The vehicle models that were replaced by EVs most are: Honda Accord, Toyota Prius, Toyota Camry, Honda Civic, Toyota Corolla, Nissan Altima, and Chevrolet Cruze. This substitution pattern suggests that EVs mainly attracted consumers who were originally choosing mid-sized and fuel-efficient gasoline or hybrid vehicles, rather than gas-guzzlers such as large SUVs or trucks.

To evaluate the environmental impact of the introduction of EVs, we evaluate the total gasoline saved and CO_2 emission reduction from EVs by comparing the gasoline consumption of the actual vehicle fleet with the counterfactual fleet without EVs. The existence of EVs helps saving lifetime gasoline consumption of 0.51 billion gallons, resulting in a CO_2 emission reduction up to 9.94 millions pounds.[9] If we do not estimate the substitution pattern, but assume each EV replaces a conventional gasoline vehicle of 23 mpg, the total lifetime gasoline saved would become 0.65 billion gallons, with a 12.8 billion pounds of CO_2 emission reduction. Simply assuming EVs replace a gasoline vehicle of an average mpg would overestimate the environmental benefits of EVs by 27%. The overestimated portion would be larger if EVs replace more fuel-efficient vehicles such as hybrid vehicles.

2.5.2 Impact of Income Tax Credits

The federal government has adopted several policies to support the EV industry including providing federal income tax credits for EV purchase, R& D support for battery development, and funding for expanding charging infrastructure.

[9] Assuming the lifetime VMT for all cars is 195,264. In reality, EVs might have a larger VMT than gasoline cars due to lower fuel cost or a lower VMT due to limited range and inconvenience of charging.

[21] estimates that the total budgetary cost for those policies will be about $7.5 billion through 2017. The tax credits for EV buyers account for about one-fourth of the budgetary cost and are likely to have the greatest impact on vehicle sales. Under the tax credits policy, EVs purchased in or after 2010 are eligible for a federal income tax credit up to $7,500. Most popular EV models on the market are eligible for the full amount. The credit will expire once 200,000 qualified EVs have been sold by each manufacturer. In 2014, the federal spent 725.7 millions dollars in providing EV buyers with the income tax credit. In order to examine the effectiveness of the income tax credit policy in terms of stimulating EV sales, we use our parameters estimates to stimulate the counterfactual sales of EVs that would arise in the absence of the tax credits to EV buyers in 2014. The counterfactual sales could help us identify the percentage of "non-additional" EV sales and also evaluate the environmental benefits of the policy. The resulting sales increase in gasoline and hybrid vehicles could help us evaluate the environmental benefits of the "additional" EV sales. The short-run benefits could be small if the additional sales simply come from people who were considering buying other fuel-efficient vehicles.

The simulation results of the market impact of EV subsidy are summarized in Table 2.9. If removing the federal income tax credits, the EV sales would decreased by 28.8% in 2014, with BEVs experiencing a sales reduction of 32.6% and PHEV sales falling by 24.5%. The results suggest that about 70% of the EV buyers would still purchase EVs even without income tax credits.

If there were no federal-level EV subsidy, 78.9% of the "additional" EV buyers would switch to gasoline vehicles with an average fuel economy of 27.2 mpg, and 11.8% would switch to hybrid vehicles with an average fuel economy of 45 mpg, with the remaining switching to diesel and flex-fuel vehicles. By inducing consumers to switch to more fuel-efficient EVs, the income tax credit policy leads to a lifetime gasoline consumption of 0.15 billion gallons and CO_2 emission reduction of 2.91 billion pounds, which is equivalent to reducing 1750 gasoline vehicles of an average fuel economy of 23 mpg. If we assume each EV replaced an conventional gasoline vehicle with a fuel economy of 23 mpg, the gasoline consumption saved would become 0.19 billion gallons and the CO_2 emission would become 3.74 billion pounds, equivalent to removing 2250 gasoline cars from the road. Not taking account of the actual substitution pattern would over estimate the environmental benefits by 27% (Table 2.10).

Table 2.11 summarizes the environmental benefits of EV income tax credits by evaluating the external cost savings from emission reduction of various pollutants. In 2014, the EV subsidy results in a total environmental benefits of $73.8 million from a more fuel-efficient vehicle fleet, by taking account of the reduction of CO_2, VOC, NO_x, $PM_{2.5}$, and SO_2. The environmental benefits are much lower than the total spending of $725.7 million since the majority of the subsidies are non-additional and the additional portion mainly induces consumers who would purchase a fuel-efficient vehicles anyways to switch. The current subsidy policy offers equal tax credits amount to all buyers of the same electric model. Alternatively, more credits could be given to lower-income households with no tax credits given to the highest-income group households. This policy design would mimic the policy reform of California Clean Vehicle Rebate Program which intends to direct the incentives towards households who are most likely to value the rebates the most. The subsidy could also target first-time buyers, who may not have a good sense of vehicle fuel consumption but are more sensitive to upfront costs.

2.6 Conclusion

Promoting electric vehicles is considered as an effective way to increase the vehicle fleet fuel economy and reduce emissions from on-road transportation. The environmental benefits of subsidizing EVs critically hinge on the fuel efficiency of the substitute vehicles. Simply subsidizing consumers who would otherwise purchase another fuel-efficient vehicles to switch to EVs would not lead to significant emission reduction. The paper provides to our knowledge the first empirical analysis of the substitution pattern of EVs with other fuel types. Our simulation results suggest that 78.7% of EVs replace gasoline vehicles with an average fuel economy of 27.2 mpg and 12% of EVs replace hybrid vehicles with an average fuel economy of 45 mpg. If we ignore the substitution pattern but simply assume each EV replaces a gasoline vehicle of 23 mpg, we would overestimate the environmental benefits of EVs by 27%. In 2014, the federal-income tax credits lead to a 28.8% increase in the sales of EVs, the majority of which replaced vehicles that are relatively fuel efficient. The increased EV sales translate to a total of environmental benefits up to $73.8 million due to reduced emissions of major air pollutants. The total subsidy spending of the income tax credit policy in 2014 far exceeds the environmental benefits of the program since about 70% of consumers would purchase EVs even without the subsidy and the subsidy also mainly attracted consumers who would otherwise purchase mid-sized gasoline or hybrid vehicles which are already fuel efficient. Our findings suggest that policy designs that intend to promote the EV technology and reduce emissions should target marginal buyers and encourage more consumers who would purchase gas-guzzlers such as large SUVs to adopt EVs.

Table 2.1: History of hybrid and EVs

years	Percentage of hybrid	Percentage of EVs	Percentage of hybrid and EVs	No. of hybrid Models Offered	No. of EV models offered
2000	0.054	0.000	0.054	2	0
2001	0.118	0.000	0.118	2	0
2002	0.213	0.000	0.213	3	0
2003	0.285	0.000	0.285	3	0
2004	0.492	0.000	0.492	4	0
2005	1.234	0.000	1.234	8	0
2006	1.521	0.000	1.521	10	0
2007	2.150	0.000	2.150	15	0
2008	2.365	0.000	2.365	17	0
2009	2.766	0.000	2.766	21	0
2010	2.373	0.003	2.376	30	2
2011	2.091	0.139	2.230	33	4
2012	3.010	0.367	3.376	44	11
2013	3.191	0.626	3.817	50	17
2014	2.748	0.723	3.471	50	22

Table 2.2: Vehicle emissions 100 miles (National average grid mix)

Vehicles	GHG gas emissions
Gasoline	87 lb CO2
Hybrid Electric	57 lb CO2
Plug-in Hybrid Electric	62 lb CO2
All electric	54 lb CO2

Data source:AFDC.

Table 2.3: Summary of Consumer Survey Data

	2010		2011		2012		2013		2014		All Years	
Variables	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Household income (1,000$)	146.78	107.92	160.10	134.60	130.65	104.49	136.78	115.16	136.21	107.96	140.45	114.16
Houshold size	2.62	1.21	2.67	1.20	2.71	1.23	2.66	1.21	2.65	1.21	2.66	1.21
With a college degree	0.62	0.49	0.62	0.49	0.63	0.48	0.65	0.48	0.65	0.48	0.64	0.48
Living in an urban area	0.65	0.48	0.64	0.48	0.66	0.47	0.66	0.47	0.68	0.47	0.66	0.47
Average commuting time (mins)	25.78	5.81	25.57	5.84	25.48	5.78	25.72	5.75	25.52	5.67	25.60	5.76
Average gasoline price ($)	2.75	0.16	3.42	0.42	3.65	0.27	3.67	0.22	3.57	0.23	3.48	0.40
Average vehicle price (1,000$)	31.17	11.39	32.00	11.49	33.16	11.28	34.19	12.84	34.98	14.00	33.46	12.54
Average MPG of the vehicle	23.38	5.57	28.51	18.65	36.80	27.87	39.78	27.05	38.06	25.56	34.81	24.50
Purchasing a light truck	0.49	0.50	0.49	0.50	0.41	0.49	0.36	0.48	0.41	0.49	0.42	0.49
Observations	1,509		1,860		2,287		2,899		3,073		11,628	

Table 2.4: Parameter Estimates in Mean Utility

	(1) OLS		(2) IV	
	Coefficient	S.E.	Coefficient	S.E.
constant	-2.4560	0.1028	-2.4728	0.1113
log(price)	-1.3497	0.2572	-1.7375	0.8164
horsepower/weight	1.9525	0.3211	2.2664	0.6870
weight	1.3393	0.2505	1.2943	0.2606
gallons/mile	0.1805	0.1283	0.1327	0.1529
AFV dummy	-3.6229	0.5823	-3.6632	0.5942
EV dummy	-2.9321	0.2652	-2.8913	0.2791
pickup dummy	0.4192	0.2863	0.7285	0.6828
model year 11 dummy	0.2743	0.1143	0.2763	0.1144
model year 12 dummy	0.3127	0.1075	0.3321	0.1153
model year 13 dummy	0.0559	0.1063	0.0687	0.1098
model year 14 dummy	0.1741	0.0920	0.1768	0.0929

Table 2.5: Parameters Estimates in Heterogeneity Component

	Coefficient	S.E.
Observed Heterogeneity		
log(price)/income	-9.0659	0.4839
family size*vehicle weight	0.0892	0.0207
urban*pickups	-0.6678	0.0561
urban*EV	0.2305	0.0482
gasoline price*gallons/mile	-0.3078	0.0234
education*EV	0.8309	0.0808
stations*EV	0.6728	0.1022
Random coefficients		
gallons/mile	1.9291	0.0565
horsepower/weight	1.0865	0.0396
light trucks	0.2823	0.0254
AFVs	0.9493	0.0886
Own-price Elasticity	-2.67	

Note: the number of observations are 11628. log-likelihood at convergence: -144129.38. 150 Halton draws are used for simulating the unobserved heterogeneity. The instrument variables used to estimate the linear parameters are the difference and squared difference in characteristics with other products in the same firm and in other firms.

Table 2.6: A sample of own- and cross-price elasticities

Products	Nissan Sentra	Chevrolet Cruze	Honda Civic	Ford Focus	Nissan Leaf	Tesla Model S	Chevrolet Volt	Toyota Prius	Honda Accord	Ford F-150	Price in 2014
Nissan Sentra (gas)	-3.01	0.06	0.06	0.06	0.05	0.03	0.04	0.05	0.05	0.02	13,351
Chevrolet Cruze (gas)	0.07	-2.95	0.07	0.07	0.06	0.04	0.05	0.06	0.06	0.02	19,243
Honda Civic (gas)	0.12	0.11	-2.91	0.11	0.10	0.07	0.08	0.09	0.09	0.03	20,106
Ford Focus (gas)	0.07	0.06	0.06	-2.97	0.05	0.04	0.05	0.05	0.05	0.02	20,026
Nissan LEAF (BEV)	0.01	0.01	0.01	0.01	-2.83	0.02	0.03	0.03	0.01	0.00	29,799
Tesla Model S (BEV)	0.00	0.00	0.00	0.00	0.01	-2.37	0.01	0.01	0.00	0.00	74,935
Chevrolet Volt (PHEV)	0.01	0.01	0.01	0.00	0.02	0.01	-2.66	0.01	0.00	0.00	35,203
Toyota Prius (HEV)	0.04	0.04	0.03	0.03	0.10	0.07	0.09	-2.68	0.03	0.01	24,027
Honda Accord (HEV)	0.12	0.12	0.12	0.12	0.10	0.09	0.10	0.10	-2.67	0.04	24,436
Ford F-150 (gas)	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	-2.53	29,806

Table 2.7: Elasticity Estimates by Fuel Type

	BEV	PHEV	Hybrid	Gasoline	Diesel	FFV
BEV	0.013	0.018	0.015	0.004	0.003	0.002
PHEV	0.012	0.011	0.009	0.002	0.002	0.002
Hybrid	0.037	0.036	0.029	0.009	0.007	0.006
Gasoline	0.028	0.027	0.028	0.029	0.026	0.027
Diesel	0.003	0.004	0.004	0.006	0.007	0.007
FFV	0.012	0.012	0.013	0.021	0.024	0.024
Own Price Elasticity	-2.751	-2.649	-2.705	-2.761	-2.606	-2.680

Note: the table summarizes the sales-weighted average own- and cross-price elasticity estimates by fuel type. For example, in average, a one percent increase in a BEV model will increases the sales of other BEV models by 0.013%.

Table 2.8: Sales Impact of Removing EVs

Fuel types	Sales change	Percentage	Average MPG
Gasoline	86114	78.7%	27.2
Hybrid	13167	12.0%	45.1
Diesel	2594	2.4%	27.4
FFV	7574	6.9%	22
All non-EVs	109449	100%	28.9

Among gasoline vehicles	Sales change	Percentage
low mpg (<19)	1972	2.3%
medium mpg (>19 & < 25)	20409	23.70%
high mpg (>25)	63733	74.0%

Table 2.9: Sales Impact of Removing EV Subsidy

Fuel types	Sales change	Percentage change		
EV	-31501	-28.8%		
BEV	-18861	-32.6%		
PHEV	-12640	-24.5%		
Other fuel types	Sales change	Percentage Change	Percentage of EV sales reduction	Average MPG
Gasoline	24867	0.23%	78.9%	27.2
Hybrid	3728	0.92%	11.8%	45
Diesel	741	0.17%	2.4%	27.5
FFV	2165	0.15%	6.9%	22
All non-EVs	31501	0.24%	100%	28.9

Note: the table summarizes the market impact of removing the federal-level income tax credit for EVs.

Table 2.10: Environmental Benefits and Substitution

Actual benefits	
Gasoline consumption saved (billion gallons)	0.15
CO_2 emission saved (billion lbs)	2.91
Equivalent gasoline cars reduction	1750
Benefits if assuming replacing a 23 mpg gasoline car	
Gasoline consumption saved (billion gallons)	0.19
CO_2 emission saved (billion lbs)	3.74
Equivalent gasoline cars reduction	2250

Table 2.11: Environmental Benefits of EV Subsidy

Pollutants	Reduction (tons)	Damage ($/ton)	Damage reduction (million $)
CO_2	1,321,767.1	36.0	47.6
VOC	3,695.2	1,482.0	5.5
NO_x	2,478.3	6,042.0	15.0
$PM_{2.5}$	14.8	330,600.0	4.9
SO_2	25.2	35,340.0	0.9
All			73.8

Note: the table summarizes the environmental benefits of the federal-level income tax credit for EVs. with a total spending of 725.7 million dollars in 2014.

Figure 2.1: Monthly EV Sales and Shares of New Car Sales in the U.S.

Note: The monthly EV sales plotted include both BEV and PHEV sales. Data source: Hybridcars.com monthly sales dashboard.

Figure 2.2: Own-price elasticity estimates

CHAPTER 3

THE IMPACT OF DISCRETE ATTRIBUTE BASING IN FUEL ECONOMY REGULATIONS

Many public policies feature policy differentiation by providing differentiated incentives or imposing unequal compliance burdens across different subjects, mainly for equity, efficiency or political reasons. For example, in the United States, the earned income tax credit (EITC) only applies to households with annual income below certain thresholds and the exact credit amount depends on the recipient's income and number of children.[1] The property tax, imposed by local governments on real estate, bases the tax amount on the market value and usage of the property, and properties owned by governments, non-profit organizations, senior citizens and veterans are often completely or partially exempt from property taxes. Since policy differentiation can be easily integrated into a existing policy system, it serves as a popular tool for policy makers to redistribute compliance burden or deliberately alter certain behaviors to achieve specific goals.

In the realm of environmental regulations, policy differentiation figures prominently and is often conducted in the form of attribute basing. Attribute-based regulations (ABRs) aim to regulate product offerings or firm behaviors by basing the standard or the stringency of the regulation on one attribute of the product or the firm. Examples include the energy efficiency standards for home appliances in the U.S.[2] and fuel economy regulations across the world,

[1] In 2017, the maximum credit for families with one child is $3,400, while the maximum credit for three or more children is $6,318. Similar programs include the public housing program that provides rental housing only for low-income families, managed by the U.S. Department of Housing and Urban Development (HUD).

[2] In the U.S., the energy efficiency standard for refrigerators depend on the attributes such as manual or automatic defrosting and whether having an automatic icemaker, and the standard

whose stringency is based on either vehicle weight or footprint.[3] The often-cited vintage-differentiated regulations (VDRs) and spatial-differentiated regulations (SDRs) are also special cases of attribute basing with the regulation stringency being based on a temporal attribute (dates of entry) or a spatial attribute (geographical locations) of the subject [92, 9]. One common feature of ABRs are that they often target one attribute of a product that is directly related to the externalities that the policies intend to reduce (emissions), while basing the regulation stringency on a secondary attribute that is not the intended target (vehicle weight), primarily for the purpose of equalizing the marginal costs of regulatory compliance across different sources. However, the difference in the regulatory stringency based on the secondary attribute creates an incentive for market participants to manipulate the attribute in order to receive favorable policy treatment, resulting in social welfare loss due to distortion in the choice of the secondary attribute [52].

This study aims to empirically investigate the welfare implication of ABRs in the context of U.S. Corporate Average Fuel Economy (CAFE) standards by focusing on the attribute basing on a discrete characteristic:[4] whether the vehicle is categorized as a passenger car or a light truck.[5] Before the introduction of the footprint-based standards in 2012, the fuel economy regulation in the U.S.

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for air conditioners depend on their cooling capacity and whether they have reverse cycles.

[3]The fuel economy standards in Europe, China, and Japan are based on vehicle weight with heavier vehicles subject to a lower MPG target. Since 2012, the Corporate Average Fuel Economy (CAFE) standards in the U.S. have become footprint-based and footprint is defined as the wheelbase multiplied by track, in square feet, which approximately measures the size of the rectangle defined by the four wheels. Vehicles with a larger footprint are subject to a less stringent target.

[4]As opposed to attribute basing on a continuous variable such as vehicle size or weight weight.

[5]Passenger cars mainly include sedans, hatchbacks, convertibles and wagons that are primarily for transporting no more than 10 individuals. Light trucks are truck-based vehicles with maximum gross vehicle weight rating (GVWR) less than 8,500 lbs. Light trucks include minivans/vans, SUVs and Pickup trucks. Starting model year 2012, 2-wheel-drive SUVs with GVWR less than 6,000 lbs are classified as passenger cars instead of light trucks.

has always been attribute-based since its initial implementation in 1975. Under CAFE, vehicles are classified as either passenger cars or light trucks. Light trucks have been subject to a lower fuel economy standard, with about 6-8 lower in mpg (Figure 3.1). On May 7, 2010, the Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) jointly developed a coordinated national program, which established greenhouse gas emission (GHG) standards and CAFE standards that allow manufacturers to build a single national fleet to meet requirements of both programs for model years 2012 through 2016. The joint rule sets additional attribute-based standards where the exact target for a vehicle depends on its footprint. Larger vehicles are subject to less stringent emission or fuel economy targets, and light trucks are still assigned a separate set of footprint-based standards which are less stringent than those for passenger cars. For example, in the GHG standards for Model Year (MY) 2016, light trucks are allowed to emit 30.3-71 more grams of CO_2 per mile than passenger cars of the same footprint (Figure 3.2). Since automakers adjust vehicle prices in the short run to make the sales-weighted average fuel economy compliant with the regulation, the fuel economy standards work as a revenue-neutral "feebate" that taxes inefficient vehicles and subsidizes efficient vehicles. By being subject to a less aggressive standard, the vehicles that are classified as light trucks are therefore being subsidized relative to passenger cars.

The rationale behind this standard split between cars and trucks dates back to the 1970s when CAFE was initially designed. At that time, light trucks were mostly comprised of pickup trucks and mainly used for small commercial and farming purposes. Policy makers did not want to impose a larger compliance burden to those buyers. However, the majority of light trucks sold on the market are used for personal transport nowadays, not for agriculture or small businesses.[6] The fleet composition has evolved dramatically to meet the growing demand for light trucks. With the increasing market share of SUVs, which are classified as light trucks under CAFE, the market share of light trucks has increased from about 20% in the 1970s to almost 60% in 2016 (Figure 3.3). Since consumers might choose between several vehicle models which fall into both the car and truck category, switching between vehicle segments is more likely to happen than 40 years ago. Although the primary goal of CAFE is to increase the fleet fuel economy to address the externalities associated with gasoline consumption, the differential treatment of cars versus trucks could distort consumer vehicle choice by encouraging more buyers to purchase light trucks, exacerbating the emission and accident externalties associated with light trucks, and impeding the progress of raising the average fleet fuel economy (Figure 3.3). ABRs are often justified by efficiency benefits of reducing the disparity of compliance burden across different sources. However, two new provisions under the joint program after MY 2012 muted the efficiency benefits of separating the standards between cars and trucks. First, the joint program implements footprint-based standard by setting less stringent targets for larger vehicles, which takes account of the compliance cost differences due to technological constraints. Second, the joint program features credit trading between truck and car fleets within firms and across firms, which should make the marginal cost of reducing one unit of emissions equal across vehicles. The provision of credit-trading thus eliminates

[6]According to U.S. Vehicle Inventory and Use Survey, the percentage of trucks (including medium- and heavy-duty trucks) used for personal transport increased from 65.7% in 1987 to 76.7% in 2002 and the percentage used for agriculture and retail business decreased from 8.5% to 2.6% and 5.6% to 2.7% respectively. Medium- and heavy-duty trucks (with gross weight weight rating over 14,000 lbs) are mainly used for business and construction with only 0.9% used for personal transport, and they are subject to a different set of standards under the joint rule of EPA and NHTSA. The vehicle use survey was discontinued by U.S. Census Bureau in 2002. The updated percentage of light trucks used for personal transport nowadays should be much higher.

the benefit of attribute basing in improving the program's cost-effectiveness and the addition of ABR to a credit trading system will only create a welfare distortion without any benefit [52].[7]

Quantifying the policy impact of discrete attribute basing in CAFE is important for the following reasons. First, the standard split between passenger cars and light trucks fails to make consumers internalize the external cost of fuel consumption, running counter to the policy goal of CAFE in achieving the socially optimal level of fuel economy. According to U.S. Energy Information Administration, about 143.37 billion gallons of gasoline were consumed in the U.S. in 2016, setting the highest amount on record. Increasing the fuel efficiency of the vehicle fleet is a critical step in strengthening energy security and alleviating environmental damage associated with gasoline consumption. Not only does CAFE fail to discourage consumers from adopting light trucks which are less fuel efficient, the discrete attribute basing might induce additional buyers to switch from passenger cars to light trucks. Such switching can impede the progress of raising the fleet fuel economy and exacerbate the problem of local air pollution, GHG emissions and energy security, the very externalities the CAFE regulation is designed to alleviate.

Second, the implicit subsidy for light trucks created by the standard split could make households choose vehicles with a fuel economy level that is even lower than the private optimal level. Between 2012 and 2014, U.S. households on average spent $2,090- $ 2,756 (3.7%- 5.4% of total household expenditure) annually on gasoline [18]. Fuel consumption on average contributes to 29%-32.6%

[7]The regulatory agents might have realized the potential impact of car-truck classification on the fleet composition, and starting MY 2011, NHTSA has reclassified many small, 2-wheel drive, sport utility (SUVs) from the truck category to the car category. Small SUVs (less than 6,000 GVWR pounds) are now grouped with cars if with 2WD and grouped with trucks if with 4WD.

of the total owning cost of vehicles and the ratio increases as household income decreases [17]. For lower-income households, the fuel consumption could be the largest component of the vehicle owning cost when gasoline prices were as high as in 2012. Therefore, mis-optimization in vehicle fuel economy could lead to a significant welfare loss, especially for lower-income households. Choosing inefficient vehicles would leave consumers subject to a greater financial burden when gasoline price increases, due to both the increased operational cost and the decreased resell value. EPA and NHTSA estimate that consumers would save more than $3,000 over the lifetime of a MY 2016 vehicle from CAFE [33], but the fuel cost savings could be undermined if some consumers are induced by CAFE to choose larger vehicles which are less fuel efficient.

Third, attribute basing could further result in additional welfare loss if the distorted secondary attribute is associated with another externality that the regulation does not intend to target. Although light trucks are likely to better protect their occupants, driving light trucks creates externalities by imposing greater danger to other road users [41] [97] [78] [3], and an increase in the market share of light trucks could exacerbate the accident-related externalities.[8] Li(2012)[69] estimate that the accident externality imposed by a light truck amounts to be $2,444 in 2006. Anderson and Auffhammer (2014) [2] show that due to the structural difference, light trucks significantly raise the probability of a fatality in a struck vehicle, in addition to the effect of their already higher weight, and conclude that the removal of the split in CAFE standards between cars and trucks would improve welfare. Jacobsen (2013)[54] estimates the rates

[8]Light trucks are generally taller with higher center of mass and are more likely to hit the upper bodies of the occupants in a truck and car collision. When light trucks strike pedestrians, bicyclists and motorcyclists, they are also more likely to hit the upper bodies of the victims, resulting in greater injury. The stiffer and heavier body structures of light trucks make trucks transfer more force to the victims in collisions.

of fatality for collisions between different vehicle classes and his policy simulation shows that a unified CAFE standard encourages switching away from light trucks into cars, which improves overall safety substantially.

Fourth, attribute basing alters the incidence of compliance across agents and could be justified on distributional grounds [52]. Although the motive for the attribute basing in fuel economy regulations can be disputed, the attribute-based standards could constitute a form of disguised protectionism [67]. The U.S. automakers produce a disproportionately large share of light trucks (about 70% in 2016). Allowing light trucks to receive a more lenient target reduces the compliance burden of domestic producers. However, the benefits of welfare redistribution is achieved at the cost of sacrificing social welfare from the distortion in the secondary attribute, which needs to be carefully evaluated if implementing attribute basing.

Motivated by the above considerations, this study evaluates the welfare loss of CAFE standards from attribute basing on a discrete characteristic, the car-truck classification. I utilize individual transaction data and vehicle sales data of MY 2012-2014, which covers the first three years following the implementation of the compliance trading provision of CAFE. I estimate a vehicle market equilibrium model with consumer vehicle demand using a random coefficient discrete choice model in the spirit of Berry et al. (1995) [14] and a stylized automaker supply model assuming that multi-product firms engage in price competition by maximizing profits from both product and regulatory credit sales. With the estimated parameters, counterfactual exercises are then conducted to simulate the prices and sales under a uniform standard to evaluate the welfare impact of attribute basing on consumer surplus, the distribution of firm profits, and environmental and accident externalities. The simulation results show that the removal of the standard split between cars and trucks could increase the sales of passenger cars by 8.0% and decrease the sales of light trucks by 4.9%. Although the uniform standard results in a larger consumer welfare loss by making consumer's choice deviate more from their private optimal choice, the deviation is nevertheless efficient by getting closer to the social optimum and the uniform standard improves the social welfare amounting to $2.83 billion from the decrease in environmental and accident-related externalities. Surprisingly, with a more stringent target, the automobile industry as a whole actually experiences a profit increase from the increased market size as fuel-efficient passenger cars become more affordable. In addition, eliminating the standard split leads to welfare redistribution among firms, suggesting that domestic firms benefit from a profit increase of 1.8% at the expense of Asian and European firms suffering from a profit loss of 1.5% and 4.0% respectively.

The findings from this study are policy relevant and particularly timely since the EPA and NHTSA are having a mid-term review of the fuel economy standards and need to determine before April 1, 2018 whether the standards for Model Years 2022-2025, established in 2012, should be revised. Since the implementation of EPA-NHTSA joint rule, the gasoline price has decreased from $3.68 in 2012 to $2.25 in 2016, and the market share of light trucks among light-duty vehicles has increased from 50% to 60% at the same time. By providing the estimate of policy-induced sales of light trucks, the study helps policy makers revisit the differential treatment of cars and trucks in CAFE and re-evaluate its consequences on the fleet composition. Given the ubiquity of attribute basing in fuel economy regulations across the world including emerging automobile markets such as China and India, this study also provides guidance for those markets to re-evaluate the consequences of implementing attribute basing when using fuel economy regulations to alleviate environmental externalities.

In addition to its policy relevance, this paper makes the following three contributions to the literature. First, this paper adds to the literature on attribute basing. Although ABRs are ubiquitous in economic policies, there is limited economic literature examining the impact of ABR. Ito and Sallee (2016) [52] provides the first analysis of the welfare consequences of ABR by providing a theoretical framework that identifies the key parameters that determine the distortionary cost and potential benefit of attribute basing. They show that ABR would only result in welfare loss if compliance trading is allowed, which has already equalized marginal compliance costs. They also empirically identify the distortion due to ABR through bunching analysis in Japanese automobile market and they use the estimated loss function as a sufficient statistic to compare the welfare impact of ABR relative to a more efficient policy. Kellogg (2017) [58] provides a theoretical framework to evaluate the welfare loss of a fixed fuel economy standard under gasoline price violatility. He shows that although attribute-based standard builds flexibility into the regulation, the distortion in attribute caused by ABR still outweighs the flexibility benefit, extending the theoretical findings from Ito and Sallee (2016) [52] to the case of gasoline price uncertainty. By focusing on the data period after the provision of CAFE compliance trading that eliminates efficiency gain from ABR in equalizing compliance costs, I am able to directly quantify the welfare loss of ABR due to the distortion in the secondary attribute. Unlike using a loss function to approximate the welfare as in Ito and Sallee (2016)[52], which requires assumption of perfect competition or at least no policy impact on firm markups, this study directly models consumer vehicle choice and firm profit maximization with market power and compliance trading, and conducts counterfactual simulations to directly and separately quantify the policy impact on consumer surplus, firm profits and externalities.

Second, it contributes to the substantial literature about CAFE standards, which mainly focuses on the efficiency of CAFE in terms of reducing gasoline consumption, such as Goldberg (1998)[42]; Kleit (2004) [59]; Austin and Dinan (2005) [6]; Jacobsen (2013)[53]. Those studies consistently find gasoline tax could achieve the same policy goal at a much lower cost. Some studies examine the distributional impacts of CAFE and find CAFE is regressive as low-income households suffer more welfare losses than high-income households: Jacobsen (2013)[53]; Davis and Knittel (2016) [28]; Levinson (2016) [66]. Other studies examine the safety impacts of fuel economy standards, including Crandall and Graham(1989)[27]; Jacobsen (2013) [54]; Bento et al. (2017) [10]. Those studies find CAFE affects vehicle mix and vehicle weight distribution, leading to different safety implications. Few recent studies investigate the attribute-based CAFE standards by focusing on the footprint-based standards. Whitefoot and Skerlos (2012) [99] models automaker's vehicle dimension choice and finds the footprint-based standard creates an incentive for firms to increase vehicle size, undermining gains in fuel economy, with the incentive being larger for light trucks. Leard et al. (2016) [63] use a reduced-form approach to look at the effect of recent gasoline price decreases on the stringency of fuel economy requirement and find the effect is relatively small as the gasoline price mostly makes consumers switch within the same footprint. Levinson (2017) [67] point out that the change from a uniform standard to the new footprint-based standard constitutes a form of disguised protectionism, by imposing costs on imported cars equivalent to a tariff because larger cars are disproportionately assembled domestically. All of these recent studies examine the impact of the newly introduced footprint-based standards and none of them directly quantify the total welfare consequences. My study focuses on attribute basing on the discrete attribute, the car-truck classification, which has been in place since the introduction of CAFE but whose welfare impact has not been empirically evaluated.

Third, this study will contribute to the understanding of notched policies and vintage- or spatial-differentiated policies. Notches in policies essentially provide different marginal incentives among different decision makers depending on their proximity to a notch, resulting in bunching on the policy-favorable side of a notch [88, 90]. Vintage-differentiated regulations, which are common in environmental policies, assign standards for regulated units based on the units' dates of entry, with later entrants or newer sources facing more stringent regulation, potentially retarding the environmental progress by providing incentives for extending the lives of aging facilities and equipment [92]. Similar to VDRs, spatial-differentiated regulations vary regulation stringency based on locations, resulting in firm reallocation to less-regulated areas [9]. By providing empirical evidence of welfare loss from attribute basing in the context of fuel economy regulations, the findings of this paper suggest policy makers should fully assess the welfare consequences when designing regulations that intend to limit some behaviors or product dimensions but implement unequal standards or policy incentives to do so.

The rest of this chapter is organized as follows. Section 3.2 briefly describes the policy background of CAFE and the data sets. Section 3.3 uses a theoretical model with graphic illustration to demonstrate the potential welfare consequences of the discrete attribute basing. Section 3.4 sets up a market equilibrium model of vehicle demand and supply and discusses the estimation strategy. Section 3.5 presents the estimation results from the structural model. Section 3.6 conducts policy simulations to evaluate the welfare consequences of the attribute basing. Section 3.7 concludes.

3.1 Policy Background and Data

In this section, I first present the policy background about CAFE and its new changes since 2012. Next I present the data used in the empirical analysis.

3.1.1 Policy Background

CAFE standards were first enacted in 1975, following the 1973-74 Arab Oil Embargo. The Department of Transportation, through the NHTSA had the responsibility for setting and enforcing fuel economy standards since then. The CAFE standards in a given model year define the minimum level of average fuel economy that each manufacturer's fleet is required to attain, and passenger car fleet and light truck fleet have always been subject to separate standards. The fuel economy standard for passenger cars stayed at 27.5 mpg from 1990 to 2010 and the requirement for light trucks has increased gradually from 20.7 mpg in 2004 to 23.5 mpg in 2010 (Figure 3.1). In 2007, The U.S. Supreme Court determined that the EPA possesses the authority under the Clean Air Act to regulate GHG emissions from motor vehicles. On May 7, 2010, EPA and NHTSA finalized a joint rule establishing standards for CAFE and emissions of GHGs, which apply to passenger cars, light-duty trucks, and medium-duty passenger vehicles for model years 2012 through 2016. Subsequently, on October 15, 2012, EPA and

NHTSA issued standards for GHG emissions and fuel economy of light-duty vehicles for model years 2017-2025. The harmonized program allows manufacturers to build a single national fleet to meet requirements of both programs. The stringency of the regulation increases over years and the standards require a combined fleet-wide fuel economy of 48.7-49.7 mpg under NHTSA's CAFE program and a fleet-wide average emission of 163 grams/mile under EPA's GHG program in MY 2025.[9]

The joint rule sets attribute-based standard where the exact target for a vehicle depends on its footprint and vehicles with larger footprints are subject to less stringent targets. The regulatory agents believe that this design encourages the increasing of fuel economy for all vehicle sizes and discourages automakers from downsizing vehicles, creating a more equitable framework, avoiding imposing disproportionate compliance obligations for most U.S. automakers who produce larger vehicles. In addition to attribute basing on footprint, this new joint program still features differential treatment between passenger cars and light trucks as light trucks are assigned a separate set of footprint-based standards that are less stringent than those for passenger cars (Figure 3.2). Since automakers need to price in the additional cost in complying with the fuel economy regulations, the separate standards between cars and trucks potentially distorts the relative prices of passenger cars and light trucks and subsequently distorts consumer's vehicle choices.

The joint program implemented starting 2012 features great flexibility including credit banking and borrowing, and the newly-added provisions includ-

[9]NHTSA sets CAFE standards only five years at a time and the 2022-2025 standards are non-final standards that were proposed to help manufacturers better plan for future products and to be harmonized with the GHG program. The EPA and NHTSA are having a midterm review of whether the 2022-2025 standards should be revised. For the GHG program, part of the improvement is expected to be made through reduction in air conditioning leakage.

ing credit transfer between the car and truck fleets and credit trading across firms. A manufacturer's car and truck fleet that achieves a fleet-average CO_2 or fuel economy level better than the standard can generate credits. For example, GHG credits are owned for grams of CO_2 saved beyond the standard over the lifetime of the vehicles exceeding the standard and are recorded in metric tons of CO_2. Additional credits are awarded to vehicles that adopt specific alternative-fuel technologies.[10]

There is great heterogeneity in terms of firms' model offerings and the fuel efficiency technologies, therefore firms bear heterogenous compliance cost under a fuel economy regulation. Figure 3.4 plots the average fleet emission and the required GHG standard relative to the sales-weighted average footprint for each automaker's newly sold vehicles in MY 2014, separately for passenger car and light truck fleets. The length of the red dashed lines reflect the relative stringency of the standard based on each automaker's product profile. The green dashed lines represent the credit surplus if the automaker's emissions were lower than the standard. As indicated by the figure, domestic "Big Three" (General Motors, Ford, and Fiat-Chrysler) and some German firms produce relatively large vehicles while Asian firms tend to specialize in vehicles of smaller sizes. Among domestic firms, Fiat-Chrysler faces a relatively stringent regulation for both of its passenger car and light trucks fleets, while GM and Ford face a similar compliance burden in the light truck fleet but maintain a relatively fuel-efficient passenger car fleet. Due to the technology difference, automakers face unequal compliance cost for each unit of fuel economy improvement per vehicle. Jacobsen (2013)[53] estimates that the additional cost to attain the stan-

[10]For MY 2012-2016, GHG program allows electric vehicles and fuel cell vehicles to use a zero grams/mile compliance value and plug-in hybrid electric vehicles could use zero grams/mile for the use of grid electricity.

dard per MPG ranges from \$52 to \$438 per car across manufacturers for MYs 1997-2001. However, with a credit trading provision, the automakers who have a relatively fuel-inefficient truck fleet but a fuel-efficient car fleet can transfer the credits they own from their car fleet to make up for the deficits of their truck fleets. The automakers who have an overall fuel-inefficient vehicle fleets can purchase credits from firms who produce fuel-efficient vehicles that overcomply with the regulation. A competitive credit trading will equalize the marginal cost of reducing one unit of emissions across vehicles and allows the policy goal of reducing gasoline consumption and emissions to be achieved at the lowest cost.

The credit trading provision makes the U.S. CAFE standard an ideal context to investigate the welfare loss due to attribute basing since the an efficient credit trading eliminates the efficiency benefit of ABR in reducing the disparity of marginal compliance burdens and the addition of attribute basing will only result in a welfare loss [52]. To empirically quantify the welfare loss, I maintain the credit trading feature in a counterfactual analysis where the standard split between passenger cars and light trucks is removed, and resolve a new market equalibrium under the new policy scenario. Since credit trading equalizes the marginal compliance cost for each vehicle, the observed credit price also helps identifying the marginal cost for each vehicle, which solves the identification problem that marginal costs and Lagrangian multipliers cannot be separately identified in the first order condition of a constrained profit maximization problem [53].

The credit banking and borrowing provision allows automakers to bank credits from overcompliance in one year to use for compliance in future model years. The banked credits could be carried up to five years to offset future shortfalls and back in time for up to three years to cover previous deficits, which helps automakers smooth economic shocks (fluctuation of fuel prices) to marginal compliance cost across years. The empirical section of this study assumes away this banking and borrowing feature when modeling vehicle supply as it involves modeling automakers' dynamic decisions, which is beyond the scope of the paper. The implication of this abstraction will be discussed in detail in the empirical section.

3.1.2 Data

The primary data for the demand estimation is the individual transaction data from the household-level survey data of the Maritz Research U.S. New Vehicle Customer Study,[11] which is a monthly survey of households that purchased or leased new vehicles. For each individual transaction, I observe the make, model, trim, model year, fuel type, transaction year-month and transaction price. The data also provides detailed demographic characteristics of the households who purchased each vehicle including income, family size, education level, zipcode, and valuable information on the alternative vehicle models they considered while making the purchase decisions. Since including the alternative vehicle choice greatly helps identifying consumer heterogeneity parameters, I only select the transactions that list at least one alternative vehicle choice, which is the model that consumers most seriously considered.[12] In order to define a tractable

[11] The data was accessed through the secure server of Resources for the Future and was not removed from the server.

[12] The survey asks the respondents to ranks three alternative vehicle choices, but the majority of the respondents (87%) only report one alternative vehicle choice. Therefore, I only include one alternative vehicle choice as consumer 2$^{\text{nd}}$ choice when modeling demand.

choice set for each model year, I limit my analysis of the groups of consumers who report an alternative vehicle choice that is from the new vehicle choice offered in each market year. Therefore, all the consumers included in the demand estimation are assumed to choose their purchased choice and alternative choice from a single new vehicle choice set that is defined for each market year. The sample period covers MY 2012-14, the first three model-years after the implementation 2012 CAFE standards and each model year is defined as September of the previous calendar year to August of the current calendar year. For example, MY 2012 is defined as September 2011-August 2012. For computational purposes, I randomly draw a sample of 9,075 transactions from the cleaned sample after removing observations with missing observed consumer attributes or information on the purchased and seriously considered models, and end up having 2,784, 3032, and 3259 transactions for MY 2012-14 respectively. Table 3.1 summarizes the demographic information for the households who made those purchase transactions. The average household income for the survey respondents in the sample is $122,260, which is close to the average household income of $117,795 for married couples in the U.S..[13] The average household size is 2.62 and 59% of the heads of household have earned a college degree. 63% of the respondents are from an urban or suburban areas with an average commuting of 25.54 minutes and average gasoline price of $3.48 during the survey time. About 50% of the sampled households selected a light truck and the average price of the vehicles that the sampled households purchased is $29,706. The average MPG of the purchased vehicles is 25.77.

The individual transaction data is then merged with Wards data which provide detailed information on each vehicle model for each corresponding model

[13]Data source: IRS Statistics of Income, 2014.

year, including horsepower, size, curb weight, wheelbase, and fuel economy. The data set is further complemented by aggregate vehicle sales data, which provides market-level information of vehicle demand, obtained from registration data complied by IHS Automotive. The IHS data record the quarterly number of registrations for each car model, broken down by fuel type, which are aggregated to model year level to construct the market share for each vehicle model in each model year. All of the above data sets are matched at a model-fuel-type level, for example, Toyota Prius-hybrid. The total number of vehicle models that are defined in the choice set are 418, 441, and 459 respectively for MYs 2012-2014. To alleviate the concern that consumers who purchase some certain vehicle models could be over-drawn or under-drawn due to sampling issue, each individual transaction is re-weighted in the estimation with the weight defined as the ratio of the actual market share of the model that the consumer purchased to the within-sample market share of that model. The average of those sampling weights is 0.99 with a standard deviation of 0.084, indicating that in general, the sample is relatively representative of the new vehicle market.

3.2 Theoretical Background

Before introducing the empirical model to quantify the welfare impact of the discrete attribute basing in CAFE, this section provides a theoretic model to illustrate the welfare impact of attribute basing on a discrete characteristic, which distills intuition for the empirical analysis. Ito and Sallee (2016)[52] uses a theoretical framework to demonstrate the welfare impact of ABR on a continuous variable: vehicle weight. The model presented here extends their main finding to attribute basing on a discrete variable. Due to the discrete choice nature, following the setup in Holland et al. (2016)[49], I assume a discrete choice transportation model, in which consumers in the market choose between a passenger car and a light truck. The assumptions in Ito and Sallee (2016)[52] and Holland et al. (2016)[49] are maintained and the implications of the assumptions are discussed in details in those work. Most of the assumptions are made for model simplicity and tractability to help providing analytical results and main implications.

Assume that consumers obtain utility from a composite consumption good x with price being normalized to one and buying a passenger car with the emission level e_c and a light truck with the emission level e_t. The present discounted benefit of the two choices are denoted as $F_c(e_c)$ and $F_t(e_t)$ respectively. Consumers have exogenous income I, which they allocate on the vehicle and the numeraire good x. The supply side is assumed as perfectly competitive and consumers pay the car or the truck with prices equal to their respective marginal costs of production $C_c(e_c)$ and $C_t(e_t)$, and the cost function is assumed to be decreasing in its argument (higher emission, lower cost). Both cars and trucks consume fuel and there is an externality associated with fuel burning with the external cost being δ for each unit of emission level. When consumers make purchase decisions, they do not take account of the external cost from emissions. Suppose a regulator wants to reduce emissions and implements an emission standard for vehicles but base the standard on the vehicle class such that cars are allowed to emit k units and trucks are subject to a lenient target with $k + \sigma$ units of emissions. The mandate allows compliance trading between the car and truck fleets, and there will be a fine with an amount of t dollars per unit of excess emission on either the car or truck fleet if any of them fails to comply with the mandate or have a credit balance deficit. This mandate acts as a constraint for consumers and the indirect utility of buying a passenger car and buying a light truck, after substituting the budget constraint, are defined respectively as the following:

$$V_c = \max_{e_c} \quad F_c(e_c) - C_c(e_c) + I, \quad s.t. \quad e_c \le k$$
$$V_t = \max_{e_t} \quad F_t(e_t) - C_t(e_t) + I, \quad s.t. \quad e_t \le k + \sigma$$

The Lagrangeans of the above maximization problems are thus defined as the following with a single Lagrangean multiplier when compliance trading equalizes the shadow cost of the regulation:

$$\mathscr{L}_c = \max_{e_c} \quad F_c(e_c) - C_c(e_c) + I + \lambda(k - e_c)$$
$$\mathscr{L}_t = \max_{e_t} \quad F_t(e_t) - C_t(e_t) + I + \lambda(k + \sigma - e_t)$$

Following [49] and the literature of discrete choice, assuming that the choice between passenger cars and light trucks is influence by the i.i.d. random tastes drawn from the extreme value distribution with zero expected value and standard deviation that is proportional to a parameter μ, the utility of cars and trucks is then defined as:

$$U_c = V_c + \varepsilon_c,$$
$$U_t = V_t + \varepsilon_t$$

Given the assumption of the distribution of the random taste, the probability of consumers choosing a light truck is:

$$s = \frac{exp(V_t/\mu)}{exp(V_c/\mu) + exp(V_t/\mu)}$$

and the expected utility from vehicle purchase for a consumer is:

$$E[max(U_c, U_t)] = \mu ln(exp(V_c/\mu) + (exp(V_t/\mu))$$

The regulator maximizes the welfare W, which is the expected utility from vehicle purchase and expected revenue from noncompliance payments less the expected external cost from vehicle emissions, by choosing the policy parameters k, σ and t:

$$\max_{k,\sigma,t} W = \mu ln(exp(V_c/\mu) + (exp(V_t/\mu)) + t[(1-s)(e_c - k) + s(e_t - k - \sigma))] - \delta[(1-s)e_c + se_t]$$

Proposition 1 shows that the optimal policy does not involve a standard split between cars and trucks (proofs in the appendix).

Proposition 1: *Where there is compliance trading and the only regulatory goal is to target the emission externality with no distributional considerations, the optimal policy should have a uniform standard such that*:

$$\sigma^* = 0.$$

The proofs of Proposition 1 shows that with an optimal policy, the regulatory agent sets the standard at k such that the compliance credit price equals to the marginal cost of emission, and the fine payment will also be set equal to the price of the trading credit, therefore $t = \lambda = \delta$. If the fine payment is set less than the trading price, automakers would just pay the fine without increasing the fuel economy. Ito and Sallee (2016) [52] shows that when ABR is based on a continuous variable such that the ABR standard function takes the form that $k_j = k + \sigma(a)$ where a denotes the vehicle weight or size, the optimal attribute slope is zero: $\sigma'(a) = 0$. Proposition 1 coincides with their finding and extends their finding to the context of attribute basing on a discrete variable and concludes that the optimal standard split is zero. The intuition is simple, with a compliance trading which equalizes the marginal compliance cost between cars and trucks, there should not be any difference in the regulation stringency if the regulation aims to reduce emissions and the marginal damage from an additional unit of emission is equal between cars and trucks. If, however, the regulatory agent employs attribute basing by treating cars and trucks separately, there will simply be distortion in the fleet composition: a larger share of light trucks. If light trucks are associated with an additional externality that the policy does not intend to target, additional welfare loss would occur. The distortion is demonstrated via the aid of graphic illustration in Figure 3.5.

A policy intervention would cause deviation of consumer's choice away from their private optima. Suppose the private optimal choice (which is the average across consumers) without any fuel economy regulation is at (s^0, e^0), where s_0 is the market share of light trucks and e^0 is the average fleet emission level. Suppose the fuel economy regulation moves consumer's vehicle choice to (s^1, e^1) and denote the choice deviation as $\Delta s = s^1 - s^0$, and $\Delta e = e^1 - e^0$, and define the consumer welfare loss from this choice deviation as $L(s^1 - s^0, e^1 - e^0) = U(s^1, e^1) - U(s^0, e^0)$. This welfare loss could be considered as a policy compliance cost, which should be evaluated against the environmental benefits of each policy less other distortionary cost if any. Following [52], assume the loss function takes the following quadratic form for the easiness of graphic illustration:

$$L(\Delta s, \Delta e) = \alpha(\Delta s)^2 + \beta(\Delta e)^2 + \gamma \Delta s \Delta e$$

Panel (a) of Figure 3.5 depicts the impact of a uniform emission standard which is set at the level k, and there is no standard difference between passenger cars and trucks. Therefore, the standard is a constant line whose slope does not change with the market share of trucks. The original optimal choice by consumers is at (s_0, e_0), which has a higher emission level than the standard. If the standard is set higher than the original emission level such that $k > e_0$, the standard is not binding and consumer choice would stay at the original point. With a binding standard such that $k < e_0$, the choice moves to the new point (s_1, e_1), where the lowest level set of the loss function, which has the ellipse shape due to the quadratic function form assumption, is tangent to the regulation line. Bundles on the same ellipse (level set) experience the same utility loss due to choice deviation and the further away from the private optimal point, the larger the utility loss. The compliance cost is measured by the length of the vector and the compliance direction is reflected by the direction of the vector (lower e and lower s). The average emission level is now at k and the market share of light trucks is at s_1, which is lower than the private optimum. This decrease in the share of light trucks ($\triangle s^1$) is an efficient change, rather than a distortion. With a fuel economy regulation that helps internalizing the externalities of gasoline consumption, consumers would choose more fuel-efficient vehicles than in a private optimum, resulting in a decrease in the share of light trucks.

Panel (b) demonstrates the impact of an ABR based on the car-truck classification. Suppose cars are subject to a higher standard k_1 and trucks received a less aggressive target at k_2 ($k_2 > k_1$). Suppose the regulator still wants to achieve the original policy goal as in the uniform policy at (s_1, e_1) and k_1 and k_2 are set such that $s_1 * k_1 + (1 - s_1) * k_2 = k$, which means when the market share of light trucks is at the level of the optimal compliance choice under the uniform standard (s_1), the sales-weighted standard is equal to the uniform standard. The fleet average standard now depends on the fleet composition. Due to the less-stringent standard of light trucks, the fleet-average standard is become less stringent (with higher emission allowance) when the market share of light trucks increases. The new compliance choice moves to (s_2, e_2), with a higher share of light trucks and higher fleet emission level than under a uniform standard.

The attribute basing results in a smaller consumer welfare loss compared with the uniform standard since the length of the compliance vector is smaller than in the uniform standard. However, the discrete attribute basing distorts the choice of trucks, resulting in more trucks sales (from s^0 to s^2). With a steeper slope of the standard (with a larger difference between k_1 and k_2), the distortion in the share of light trucks is much larger. The reduced emissions by the attribute-based standard is also lower than the uniform standard due to higher emissions from trucks ($\triangle e^2 < \triangle e^1$).

The qualitative findings from the graphic illustration suggest that attribute basing not only runs counter to the policy goal of achieving a more efficient fleet, but also creates additional distortion in the secondary attribute. To quantify the welfare loss from the discrete attribute basing, we need to compare ABR with a uniform standard by taking account of the consumer welfare loss due to deviation from the private optima, the environmental benefits brought by each policy, and additional externalities due to distortion if any. Therefore, an empirical analysis which models both consumer vehicle choice and automaker vehicle supply is needed and is presented in the following sections.

3.3 Empirical Model and Estimation

The empirical section aims to estimate a structural model of the automobile market so that counterfactual analysis could be carried out to quantify the welfare impact of discrete attribute basing under CAFE by comparing the market outcomes with a uniform standard that removes the standard split.

By taking advantage of the individual transaction data from Maritz, I first estimate consumer demand for new cars taking into account of both observed and unobserved consumer heterogeneity in the spirit of Berry et al. (1995,2004)[14] [15], Petrin (2002) [81] and Train and Winston (2007)[94]. With the demand estimates, marginal costs are backed out assuming optimal pricing under Bertrand-Nash competition where automakers adjust prices to maximize profits from both vehicle and regulatory credit sales, taking product choices as given. This section presents the demand and supply models as well as estimation strategies.

3.3.1 Vehicle Demand Model

I define a market as the aggregated market of all the MSAs for each model year from 2012 to 2014. Within each market, households purchase one model j within the inside goods or choose the outside good, which is defined as not purchasing a new vehicle. I model vehicle purchase decision statically assuming that consumers behave myopically and make their purchase decisions based on the current price and product attributes. Due to the durable nature of vehicles, consumers might delay their purchase expecting for price drop or quality improvement in future [44]. However, unlike the markets of cellphones, computers, and digital cameras where the technology is evolving rapidly, the automobile industry is relatively mature and no technological breakthrough happened within my sample period and the vehicle price and gasoline price were also stable between MY 12-14. Thus, the benefits of delaying a purchase may not be high and assuming a static vehicle demand model may be reasonable.

Household i's utility from purchasing vehicle model j is defined as:

$$u_{ij} = \underbrace{\sum_{k=1}^{K} x_{jk}\bar{\beta}_k - \alpha_1 lnp_j + \xi_j}_{\delta_j} + \underbrace{\alpha_2 \frac{lnp_j}{Y_i} + \sum_{kr} x_{jk} z_{ir} \beta^o_{kr} + \sum_{k} x_{jk} v_{ik} \beta^u_k}_{\mu_{ij}} + \varepsilon_{ij} \tag{3.1}$$

where δ_j is the mean utility of vehicle model j which is constant across consumers in the same market. The x_{jk} stands for the k_{th} vehicle attribute for model j, and I include horsepower, weight, size, gallons per mile as the observed vehicle attributes. The price p_j is the average transaction price observed from the survey data, which is constant for a same model in all locations. The logarithm of price is employed to make the price effect decrease as the price of a vehicle model increases. The second component μ_{ij} captures heterogeneous utility driven by both observed and unobserved consumer characteristics. Y_i is household i's income in the corresponding year and $1/Y_i$ captures how a household's income influences their price sensitivity. One would expect α_2 to be negative as higher income households would be less sensitive to a price increase due to the diminishing marginal utility of money. z_{ir} denotes consumer i's other demographic variables including family size, whether living in an urban area, the average gasoline price in the area, which are interacted with certain vehicle attributes to capture variation in consumer preference due to observed heterogeneity. The unobserved consumer taste v_{ik} is assumed to have a standard normal distribution. The coefficient β_k^u can be interpreted as the standard deviation in the unobserved preference for the vehicle attribute k conditional on the consumer's observed attributes. Let $\theta_1 = \{\beta_{kr}^o, \beta_k^u\}$, denoting the "nonlinear" parameters, and it is understood that the vector $\delta = \{\delta_1, ..., \delta_j\}$ is estimated conditional on a given θ_1. The last component ε_{ij} is the idiosyncratic preference of household i for vehicle model j and it is assumed to have an i.i.d. Type 1 extreme value distribution. The Maritz data includes vehicle models that consumers seriously considered other than the purchased model, which allows for a ranking of both the first and second vehicle choice. Thus, the joint probability of household i choosing j and seriously considering h as an alternative choice when the outside option and j are removed is:

$$P_{ijh} = \int \frac{exp[\delta_j(\theta_1) + \mu_{ij}(\theta_1)]}{1 + \sum_g exp[\delta_g(\theta_1) + \mu_{ig}(\theta_1)]} \cdot \frac{exp[\delta_h(\theta_1) + \mu_{ih}(\theta_1)]}{\sum_{g \neq j} exp[\delta_g(\theta_1) + \mu_{ig}(\theta_1)]} f(v) dv \tag{3.2}$$

Instead of constructing moments exploiting the exogeneity assumption that unobserved product attributes are uncorrelated with observed attributes, I estimate the demand function using maximum likelihood as in [94, 61, 43, 98, 75]. Let $lnR_i = lnP_{ijh}$, denoting the individual log-likelihood of household i choosing the observed purchased model j and considering the observed alternative choice h. The log-likelihood function of the entire sample for a single market is therefore:

$$lnL = \sum_{i=1}^{N} lnR_i \tag{3.3}$$

The nonlinear parameters θ_1 are estimated via maximum likelihood by maximizing the likelihood function above. To reduce the dimensionality of the coefficient space, I do not directly maximize the likelihood over the entire space of (θ_1, δ) but back out the mean utility δ conditional on θ_1 using market share inversion as in [12]. Define the probability of observing household i choosing model j as:

$$P_{ij} = \int \frac{exp[\delta_j(\theta_1) + \mu_{ij}(\theta_1)]}{1 + \sum_g exp[\delta_g(\theta_1) + \mu_{ig}(\theta_1)]} f(v)dv$$

The market demand is then the sum of individual consumers' demand and the predicted market share is obtained by calculating P_{ij} with parameters θ_1 and δ and averaging over the N consumers in the survey sample. The mean utility fixed effects δ are solved by matching the observed market shares from the aggregate sales data to those predicted by the model:

$$S_j = \hat{S}_j(\theta_1, \delta(\theta_1, S)) = \sum_n P_{ij}(\theta_1, \delta)/N \tag{3.4}$$

I estimate δ by contraction mapping following [14] and δ is calculated for each trial value of $\hat{\theta}_1$ in the numerical search for the maximum of the log- likelihood function:

$$\delta_j^t(\hat{\theta}_1) = \delta_j^{t-1}(\hat{\theta}_1) + ln(S_j) - ln(\hat{S}_j(\hat{\theta}_1, \delta_j^{t-1}(\hat{\theta}_1))) \tag{3.5}$$

After estimating $\hat{\theta}_1$ and $\hat{\delta}(\hat{\theta}_1)$, the "linear" parameters $\theta_2 = \{\alpha_1, \bar{\beta}_k\}$ are estimated using IV-GMM given the following specification:

$$\delta_j = -\alpha_1 lnp_j + \sum_{k=1}^{K} x_{jk}\bar{\beta}_k + \xi_j$$

where ξ_j denotes the unobserved vehicle attributes of model j. To control for the correlation of price with the unobserved product attributes, following Train and Winston (2007) [94] , I use BLP-style instruments Z_j that measures the sum of distance and squared distance in attribute space between own product and other products in the same firm and from other firms. θ_2 is estimated using GMM solving the following minimization problem:

$$\min_{\theta_2} \quad G_J(\theta_2)' W G_J(\theta_2) \tag{3.6}$$

where J is the total number of models, W is the weighting matrix and $G_J(\theta_2)$ is the sample analog of the moment condition defined as:

$$G_J(\theta_2) = \frac{1}{J} \sum_j \hat{\xi}_j Z_j$$

3.3.2 Vehicle Supply

Vehicle manufacturers could meet tighter CAFE standards by adopting fuel-saving innovations, by lowering the relative price of fuel-efficient vehicles and reducing weight or adjusting other vehicle attributes. In this study, I only allow firms to adjust sales mix by changing prices to maximize the profit from both vehicle sales and regulatory credit sales holding the models introduced and vehicle characteristics constant. This "mix-shifting" strategy is a common practice that automakers adopt in complying with the fuel economy regulation. Jacobsen (2013) [53] tests the assumption of "mix-shifting" by exploiting time-series variation in the stringency of CAFE at the firm level and his findings strongly support this firm behavior: fuel-inefficient vehicles are priced higher and fuel-efficient vehicles are priced lower when the standard is more binding. Although there is evidence that automakers could redesign a vehicle model to make it classified as a light truck to take advantage of the preferential treatment of light trucks,[14] this paper only focuses on the short-run impact of the standard split within a specific model year, and transforming a passenger car to a light truck involves significant vehicle redesign such as significantly increasing GVWR (weight), squeezing in a third row of seats or converting 2WD to 4WD which takes a much longer production phase [77].[15] Besides, the number of light truck models introduced was quite stable during MY 2012-14, which my data period covers. Therefore, only allowing automakers to adjust price is a reasonable assumption for the scope of this paper and endogenizing automaker's decision in vehicle attributes is relevant for investigating the long run impact of

[14] Examples include Subaru's 2004 Outback four-door sedan, Chrysler's PT Cruiser, and Lexus NX 300h, which all retain certain dimensions of a car but were classified as light trucks. The practice helped the automakers improve their light truck average fuel economy.

[15] According to NHTSA (2010)[77], even increasing the footprint requires platform changes, which usually occurs once every 5 years.

the discrete attribute basing on the automobile industry.

The vehicle supply follows Berry et al. (1995)[14] with the modification of adding the revenue from regulatory credit sales from the GHG program. Since the national program is harmonized to allow automakers to build one single vehicle fleet that satisfies both CAFE and GHG standard requirements, only GHG credits sales, whose credit prices are observed, are modeled for simplicity.[16] An automaker f is assumed to face a profit-maximization problem that maximizes the profit from both vehicle sales and sales from regulatory credits, which is defined as follows,

$$\max_{p_j, j \in J_f} \pi^f = \sum_{j=J_f} [p_j q_j(P) - vc_j(q_j)] + \lambda \sum_{j \in J_f} (t_j - e_j) VMT_j \cdot q_j(P), \tag{3.7}$$

$$t_j = \begin{cases} \mu_c + \gamma_c a_j, & j \in C \\ \mu_t + \gamma_t a_j, & j \in T \end{cases}$$

where J_f is the set of all the vehicle models produced by firm f. vc_j is the total variable cost of producing model j, p_j is the price and q_j is the sales for product j. P is the vector of prices of all the vehicle models in the market. e_j is the CO_2 emission for vehicle model j and t_j is the emission target for model j depending on j's footprint a_j and whether it is classified as a car C or a light truck T. Corresponding parameters μ_c and γ_c or μ_t and γ_t are plugged into the equa-

[16]The credit trading prices are not observed for the CAFE program. The vehicle supply modeling here assumes that the two programs are equivalent. However, there are some differences between CAFE and GHG programs, which are summarized in Leard and McConnell (2017)[64]. If the two programs are not fully harmonized, prices observed in the credit trading market of one program will not reflect the marginal costs of compliance for the two programs.

tion of t_j to obtain the emission targets for each vehicle model. VMT_j is the total miles traveled over the life cycle of model j. EPA assumes that the lifetime VMT_j is 195,264 miles for cars and 225,865 miles for trucks. λ denotes the equilibrium credit trading price. Since the new joint rule starting in 2012 allows credit trading between car and truck fleets within the same firm and also across firms, there is only one equilibrium price for each unit of credit. The second summation in Equation (7) denotes the total credit sales, which is positive if firms generate revenue from producing excess credits and is negative if firms loss revenue from buying credits from other firms to make up for credit shortage. The model here assumes away credit banking and borrowing, and automakers are required to use the credits generated within the current model year to comply with the regulation and are required to offset a negative balance by purchasing credits from other firms. Under the current joint program, automakers are allowed to bank credits for up to five years and carry back credits to offset previous deficits up to three years. The flexibility intends to help automakers harmonize compliance burden from year-to-year fluctuations of market shocks including changing fuel prices. For example, if a gasoline price drop makes consumers choose more vehicles that are less fuel-efficient, using banked credits to make up for credit shortage or carrying deficits and borrowing future credits could reduce firm's compliance burden in that affected year. Therefore, assuming away the feature of credit banking and borrowing increases firms' compliance cost and would potentially overestimate the policy impact. However, my data period MY 2012-14 witnessed a relatively stable gasoline price (around $3.5 per gallon in average) and the gasoline price plummeted starting October 2014, which is right after MY 2014 that is defined till August 2014. As long as the demand is stable and there is no market shock that significantly affects firms' compliance strategies across years, the static period-by-period should coincide with the dynamic solutions that incorporates credit banking and borrowing [53].

The first-order condition of the firm profit defined in Equation (7) with respect to model j's price p_j is:

$$q_j(P) + (\sum_{r \in J_f} p_r - \sum_{r \in J_f} mc_r - \lambda \sum_{r \in J_f} (e_r - t_r) VMT_r) \frac{\partial q_r}{\partial p_j} = 0, \quad \forall j$$

The above systems of equations can be written in a matrix form as follows,

$$Q(P) + \Delta[P - MC - \lambda(E - T)VMT] = 0$$

$$P = -\Delta^{-1} Q(P) + MC + \lambda(E - T)VMT \tag{3.8}$$

where Δ is a J by J matrix where J is complete set of all vehicle models in a model year and the element of Δ are:

$$\Delta_{jk} = \{ \begin{array}{l} \frac{\partial q_j}{\partial p_k} \text{ if products j and k are produced by same firm} \\ 0 \text{ otherwise} \end{array}$$

and the elasticity element in the Δ matrix can be estimated as:

$$
\frac{\partial q_j}{\partial p_j} = M \cdot \frac{\partial s_j}{\partial p_j} = M \cdot \frac{\sum_{i=1}^{N} \frac{\partial s_{ij}}{\partial p_j}}{N} = M \cdot \frac{\sum_{i=1}^{N} -\alpha_i s_{ij}(1 - s_{ij})}{N}
$$
$$
\frac{\partial q_j}{\partial p_k} = M \cdot \frac{\partial s_j}{\partial p_k} = M \cdot \frac{\sum_{i=1}^{N} \alpha_i s_{ij} s_{ik}}{N}
$$

where M denotes the market size. With the Δ matrix estimated and λ obtained from the credit trading market, I can back out marginal cost for each model j. Without λ, marginal cost and the credit price cannot be separately identified. For the trading credit values, I use the GHG credit price estimated in Leard and McConnell (2017) [64], which are 36, 63, and 42 \$/Mg respectively for MY 2012-2014.[17]

$$
MC = P + \Delta^{-1} Q(P) - \lambda(E - T) VMT \tag{3.9}
$$

This first-order condition differs from a profit maximization problem without credit trading by having an extra term interacted with the credit price. If there is no credit trading, the credit price will be zero and the first-order condition will be the same as in a Bertrand price competition case for oligopolies. With a positive credit price, there will be an additional cost for the vehicles whose emissions are above the required level and an additional revenue from selling the vehicles whose emissions are below the required level. Therefore, with credit trading, the fuel economy regulation works as a revenue-neutral tax system by taxing fuel-inefficient vehicles and subsidizing fuel-efficient vehicles. Under the original CAFE system before 2012, there were three types of firms as

[17][64] calculate the GHG credit price from the revenue of GHG credit sales by Tesla, and the settlement between Hyundai and Kia and EPA and US Department of Justice concerning the two automakers' violation of the Clean Air Act.

summarized in Jacobsen (2013)[53]: (i) firms with fleet fuel economy exceeding the standard and therefore the constraint is not binding (ii) firms that violate the standard and pay the associated fines and face a non-constraint less-penalty profit maximizing problem and (iii) firms that are constrained by CAFE. Under the joint program starting MY 2012, the credit-trading system encourages firms who produce vehicles that overcomply with the regulation, those who were originally not constrained by the regulation, to continue increasing fuel efficiency to generate revenue from selling credits. Under the GHG program, intentionally paying fines in lieu of meeting the standard is also no longer allowed [77]. Therefore, all the three types of firms under the original CAFE program have the incentives to continue increasing fuel economy to generate credits under the new joint program and all the firms' behaviors could be modeled as a multi-product profit maximization problem with credit trading represented by the single first-order condition above (Eq. (8)).

3.3.3 Identification

This subsection discusses the identification of the demand model. The preference parameters are identified primarily through variation in the market shares corresponding to variation in the choice set across markets, variation in the observed vehicle attributes across models, and variation in observed consumer demographic attributes.

The mean utility component δ represents the average consumer utility for each vehicle model and is backed out by matching the observed market shares with the model prediction. If there is no consumer heterogeneity, all variation in market shares would be driven by variation in the observed vehicle attributes. The linear parameters $\bar{\beta}$ and α_1 in the mean utility are identified though variation in market shares corresponding to the variation in price and other observed vehicle attributes (such as vehicle size). Due to the potential correlation between unobserved vehicle attributes ξ_j with price p_j as automakers observe ξ_j when choosing prices, instruments that capture the extend of price competition are used to correct for potential endogeneity. More specifically, following Train and Winston (2017)[94] and Langer (2012)[61], I use BLP-style instruments as the sum of the difference in attribute space between the vehicle and all others sold by the same firm and all others sold by other firms, and also the sum of the squared differences. Those distance instruments measure the competition pressure that automakers face when pricing each model, which provides exogenous variation in price that aids the identification of consumer average price sensitivity.

The consumer heterogeneity component includes both the observed heterogeneity portion that could be explained by observed consumer attributes and the unobserved heterogeneity portion that are related to unobserved consumer tastes. Consumers have heterogenous preference and therefore different vehicle models would attract consumers with different tastes. The parameters β^o_{kr}, which are associated with observed consumer attributes, are identified with the aid of demographic information observed for different households who purchased different vehicle models. For example, if we observe households with a larger family size disproportionately purchased larger and heavier vehicles, we would expect a positive coefficient for the interaction between family size and vehicle weight. Variation in the transaction prices of the purchased vehicles across different income groups helps identifying the parameter α_2. If higher income groups tend to be less price sensitive to vehicle prices and disproportionately buy more expensive vehicle models, we would expect a negative sign for α_2, which captures the impact of income on consumers' price sensitivity.

The unobserved consumer heterogeneity parameters β_k^u governs the substitution pattern and are identified by the substitution patterns observed from both the macro and micro-level data. At the macro data level, variation in the market shares corresponding to variation in the choice set (available vehicle models) helps identifying β_k^u. For example, if we observe a consumer purchases model A in market 1 and another consumer with similar observed consumer attributes in market 2 purchases model B when model A exits or becomes more expensive, the proximity in vehicle attributes between model A and B helps the identification of β_k^u. At the micro data level, the alternative choices that consumers considered when making purchase decisions provides valuable information in estimating consumer's substitution pattern between vehicles, which greatly assists the identification of β_k^u. The alternative vehicle choices are the choices that consumers make in a choice set where both the purchased choice and the outside option are removed. By observing each consumer's alternative choice in a hypothetical choice set that varies across consumers is similar to observing consumer's substitution with actual variation in choice sets. Since different consumers buy different vehicle models, the number of the hypothetical choice sets created by the alternative choice data equals to the number of purchased vehicle choices, which provides variation in choice sets that are much richer than that provided by macro-level data, which often relies on observing multiple markets or multiple model years. More specifically, the closeness in the vehicle attributes between the purchased vehicle choice and the alternative vehicle choice facilitates identifying the parameters β_k^u. For example, if consumers' purchased vehicles and their seriously considered alternative choices are often within a certain fuel economy range, we would expect a statistically significant coefficient for the unobserved heterogeneity parameter associated with MPG. Since my data covers only 3 markets (MY12-14) which is relatively small compared to previous applications of random coefficient discrete choice models that relies on observing a large number of markets, most of the identification of the unobserved heterogeneity parameters comes from the alternative choice information. Berry et al.(2004)[15] note that having micro-level 2^{nd} choice data greatly helps the estimation of random coefficients when they only have observations for one model year and Train and Winston (2007)[94] also mention that including alternative choice data significantly improves the precision of the random coefficient estimates.

3.4 Estimation Results

3.4.1 Demand parameters

Table 3.2 & 3.3 report the estimation results of the demand model. The mean utility δ represents the average preference consumers have for each vehicle model and are estimated via matching the model predicted market share to the observed market share. The mean preference coefficients for price and each observed vehicle attribute are recovered from GMM-IV estimation with the instruments correcting for the endogeneity of price. Both OLS and IV results are reported in Table 3.2 and reflect the preferences for vehicle attributes that are generally expected. In average, consumers have a negative preference for price and the price coefficient in the IV specification is more negative, suggesting OLS underestimates the price sensitivity. Consumers have a positive preference for acceleration, measure by horsepower/weight. Without interacting with gasoline price, the coefficient for gallons/mile is positive, suggestion average consumers do not like fuel-efficient cars but prefer cars that are more powerful. Consumers in general prefer cars that are heavier and dislike alternative fuel vehicles including hybrid and plug-in electric vehicles. Conditional on other vehicle attributes, consumers dislike vans and pickups but favors SUVs relative to passenger cars, which coincides with the evidence that the SUV segment experiences the largest sales increase among all vehicle categories in recent years. The positive signs for MY 13 and MY 14 dummies suggest that consumers prefer MY 13 and MY 14 vehicles to MY 12 models, controlling for other vehicle attributes.

Turning to the consumer heterogeneity parameters, with the aid from the individual transaction data, the interaction terms of consumer demographics with vehicle attributes are estimated precisely with intuitive signs. The coefficient of log(price) divided by income captures the extent to which a consumer's price sensitivity varies with income. The negative sign of the estimate suggests that households with lower income react more negatively to a vehicle's price than households with higher income. The elasticities implied from the price preference will be further discussed below. Compared with households who live in suburban and rural areas, households who live in urban areas are less likely to adopt pickups, probably due to less towing utility and limited parking space, but are more interested in alternative fuel vehicles (AFVs) due to both more frequent city driving needs and better refueling infrastructure provided in urban areas. Households of a larger family size prefer larger vehicles that are heavier.

The interaction of gasoline price with gallons/mile, which measures the operating cost per mile of the vehicle, has a negative sign, suggesting that consumers have a negative preference for the fuel cost.

Three random coefficients are included, which represent unobserved consumer heterogenous preference for gallons/mile, horsepower/weight, and light trucks. As indicated by the estimation results, data on consumers' alternative vehicle choices greatly helps precisely identifying those parameters. Based on the standard normal distribution of the random taste v_{ik}, the coefficient β_k^u can be interpreted as the standard deviation in the unobserved preference for the vehicle attribute k. To reduce simulation noise and bias, following Train and Winston (2007)[94], I use 150 Halton draws in the simulation of the integral over the unobserved consumer taste v. [18] All of the three coefficients are statistically significant, indicating that consumers have heterogenous preference for those vehicle attributes conditional on the observed consumer characteristics. Those precisely estimated random coefficient parameters help breaking down the I.I.A. problem experienced in traditional logit models and play a critical role in governing the substitution patterns.

3.4.2 Elasticities and Profit Margins

The demand system implies sensible elasticities and markups. All implied own-price elasticties are greater than one, ranging from -7.75 to -3.5 with an average being -5.51 and standard deviation being 0.37. The sales-weighted average elasticity among all the 1,318 products in three model years is -5.55. The magnitude

[18]Halton draws are a type of low-discrepancy sequence. The demand results are similar when the number of Halton draws are increased to 200.

of the own-price elasticities are close to those obtained in Berry et al.(1995)[14], Petrin (2002)[81], Beresteanu and Li (2011)[11] and Li (2012) [69]. Figure 3.6 plots the own-price elasticities against price and demonstrates that more expensive models tend to have less elastic demand. With the elasticity estimates, the price-cost margins are recovered. The average implied price-cost margin is 19.0% (sales-weighted average being 19.1%) of the transaction price, which is close to 24% in [14], 16.7% in [81], 17.7% in [11] and 18.13% in [69] . Figure 3.7 plots the estimated profit-cost margins against transaction prices, which demonstrates a pattern that more expensive models have a larger profit margin as they usually target consumers who have a higher income and thus are less sensitive to prices. Alternatively, products with more elastic demand tend to have lower price-cost margins than products with less elastic demand. For example, the price-cost margins for 2014 Chevrolet Spark and Porsche 911 are 16% and 22% respectively.

With the estimated implied profit-cost margins and the credit trading component, marginal costs are backed out from transaction prices using the first order condition in Equation (9), which will be used for counterfactual simulations.

3.5 Policy Simulations

To quantify the welfare impact of the discrete attribute basing in CAFE standards, I set passenger cars and light trucks subject to a uniform standard using a single footprint-based standard formula and simulate counterfactual market outcomes and compare the social welfare with the observed scenario.

3.5.1 Simulation Method

I run a counterfactual simulation where light trucks and passenger cars are subject to a uniform footprint-based standard. The footprint-based feature is still preserved, since it encourages automakers to improve fuel economy of all sizes and helps preserving the size distribution of the entire fleet by reducing the incentives for automakers to downsize the vehicles, alleviating the safety concern. Keeping the footprint-based standards instead of having one single target for all vehicles also makes the alternative policy less aggressive. The alternative policy essentially removes the differential treatment between cars and trucks with the same footprint. Since my paper focuses on the impact of attribute basing on the car-truck classification, maintaining the footprint-based feature helps me isolate the impact of the standard split between cars and trucks.

The uniform standard would use the sales-weighted average parameters for the footprint-based emission standard formula:

$$t_j = \mu + \gamma a_j, \quad \forall j$$
$$\mu = (1 - s)\mu_c + s\mu_t, \quad \gamma = (1 - s)\gamma_c + s\gamma_t$$

where s denotes the market share of light trucks. Figure 3.8 depicts the uniform footprint-based standards for MY 2014: light trucks are subject to more stringent targets and passenger cars are subject to less stringent targets. Throughout the counterfactual exercise, I assume that automakers do not change vehicle attributes other than price, and therefore the estimated results reflect the short-run impact of the discrete attribute basing under CAFE. To compare the policy impacts on consumer surplus, I compare the welfare losses of the two policies in making consumers' choices deviate from their private optima. More specifically, I estimate the monetary transfer that is need to make consumers indifferent between the choice with policy and the choice without policy for both of counterfactual and observed policy scenarios, which measures the policy compliance cost borne by consumers.

Since automakers are subject to a different standard in the counterfactual scenario, the new equilibrium regulatory credit price along with the new equilibrium vehicle prices and sales need to be resolved. The simulations are carried out through the following steps:

1. Plug the initial credit price and the initial vehicle price vector p, but the counterfactual emission target into the first order condition, as defined in Equation (8).
2. Update the price vector such that the difference between the left-hand side and the right-hand side are within a certain threshold.
3. Calculate the credits generated by each firm conditioning on the new equilibrium sales. Sum across all firms to obtain the total credits for the market. If there is excess demand (supply) for credits in the equilibrium, increase (decrease) the credit price and repeat from step (1) to find a new equilibrium.
4. If there is again excess demand (supply), further increase (decrease) the credit price and repeat the above steps until the newly searched credit price clears the credit trading market.

3.5.2 Impacts on market outcomes

Under the uniform standard, the more efficient passenger car models are subject to a lower standard than before and thus receive more subsidy, while the less efficient trucks are subject to a more stringent target and thus receive a higher implicit tax. Due to the larger share of light trucks, the automaker industry is facing a more stringent regulation in general. The original credit price is too low to clear the credit trading market, inducing excess credit demand. Not surprisingly, the simulated new credit price increases to $133.1, reflecting an increase in the stringency and marginal compliance burden of the regulation. With changes in the credit price and emission targets from removing the attribute basing, automakers need to re-adjust the sales mix by increasing the sales of the vehicles which could generate more credits while balancing between the revenue from vehicles sales and credit sales. The magnitude of vehicle price and sales changes depend on the own and cross price elasticties. Table 3.4 shows the price and market share impacts of the uniform standard on different vehicle segments.

In average, the price of passenger cars decreases by $471 with the largest price reduction from battery electric vehicles (BEVs) such as Tesla Model S, Nissan LEAF, Ford Focus Electric, which would have a price reduction over $13,000. With a higher regulatory credit price, automakers rely more on BEV models to generate credits since they are the models which have the least tailpipe emissions and they are treated having zero emissions under the current regulation. The implicit subsidy under CAFE is close to the price difference between EVs and their gasoline counterparts. Having a uniform standard would make BEV models more affordable and encourage more consumers to adopt this new technology. With a higher credit price, automakers are also reducing the sales of car models which are least fuel-efficient by increasing their prices. The car models that experience the highest price hikes are Dodge Viper, Audi R8, Mercedes-Benz C63, which are all luxury sporty cars with the lowest fuel efficiency.

Without the favorable treatment for the light truck category, the prices for light trucks would increase by $2,766.2 in average. More specifically, SUVs would have an average price increase of $2,215.9, with the least price increases from SUV models that are fairly fuel efficient such as Lexus RX350, Lexus RX450 Hybrid, and Subaru XV Crosstrek Hybrid, and the largest price increases from the models which are the least fuel efficient: Mercedes-Benz G63, Lexus Lx570 and Mercedes-Benz GL63. Similar patterns are observed for the van segment. The average price increase of vans is $2,988.7 with GMC Savana Passenger Van, Ford E-150 and Ford E-350 Passenger Vans experiencing the largest price increase over $7,000. The prices for pickups would go up by $4,317.2 in average, higher than both the SUV and Van segments due to a higher emission level in general. The pickup models that are hurt most under the uniform standard are: RAM Pickup 3500 and RAM Pickup 2500. Figure 3.9 panel (a) and (b) plot the relationship between the price change under the uniform standard and fuel economy level for the passenger car and light truck segments respectively. As expected, the sign and magnitude of the price changes are highly correlated with the fuel economy levels. In general, passenger cars with higher fuel efficiency experience a larger price decrease and light trucks with lower fuel efficiency experience a larger price increase.

Removing the standard split between cars and trucks has a significant impact on the market structure of the automobile industry. The total sales in the car segment would increase by 8.0% and the total sales of light trucks would decrease by 4.9% with the sales in the SUV, van and pickup segments falling by 1.5%, 12.2%, and 11.9% respectively. The uniform standard hurts the van segment more since it has fewer models available than the SUV and pickup segments, making it easier for consumers to switch to other segments given a price increase. The SUV segment has the least percentage decrease in profit due to its largest sales base and the largest number of available model choices among the light truck category. With more models to choose from, consumers are more likely to switch from expensive SUV models to less-expensive SUV models instead of switching out of the segment. The sales decrease of the SUV segment is also likely to be offset by consumers switching from the van and pickup segments. The uniform standard affects the market structure by increasing the market share of cars and decreasing the market share of light trucks. The total market share of passenger cars increases from 46.6% to 49.7% and the market share of light trucks decreases from 53.4% to 50.3%. The decreasing price for some fuel-efficient car models increase the utility of owning new cars and makes some consumers switch from the outside good towards buying a new vehicle. The uniform standard increases the sales from the subsidized car segment more than the sale losses from truck segment that is being taxed more. This should not be surprising considering that small car buyers are more price sensitive than truck buyers and they are more likely to switch from choosing public transportation or used cars to purchasing new cars. With a stronger preference for new vehicles, existing light truck buyers are also less likely to switch to the outside option due to a higher price from the removal of the preferential treatment for trucks. The uniform standard also makes a more efficient vehicle fleet by increasing the sales-weighted average fuel economy from 26.1 mpg to 27.5 mpg, compared with the current standard that features the discrete attribute basing. This fuel economy change translates to a considerable vehicle-lifetime gasoline consumption saving up to 1.61 billion gallons discounted to MY 2014.

3.5.3 Welfare impact

This section explores the welfare impact of removing the discrete attribute basing by focusing on consequences on consumer surplus, firm profits, and externalities associated with air pollutants, emissions and accidents, which are interpreted as total vehicle lifetime changes from annual sales.

Consumer surplus

A policy intervention like the fuel economy regulation intends to alter consumer vehicle choice to help consumers internalize the externalities associated with their behaviors. An efficient policy is to improve the social welfare by reducing the external costs from the externality that the policy intends to target while minimizing the distortionary cost and the welfare loss in consumer surplus. Consumer surplus loss under the regulation could be thought as the compliance cost that consumers need to bear and is defined as the utility loss due to deviation form their private optimal choice. If a consumer purchases a vehicle that is being subsided (taxed) under CAFE while the consumer would have purchased the same vehicle without CAFE, this consumer experiences a welfare gain (loss), which is equal to the difference of consumer surplus of purchasing the model with and without the subsidy (tax). If, however, consumers are induced by CAFE to pick a model that deviates from their private optimal choice, they suffer a welfare loss, which is equal to the gap in the intrinsic utility between a consumer's top choice and the policy-induced choice. For example, if a consumer chooses a vehicle model A without CAFE, while being induced to purchase a sub-optimal model B by the relative price change due to CAFE, the consumer suffers a welfare loss which is equal to the difference between the consumer surplus obtained from the private optimal choice A and that obtained from the suboptimal choice B.

To compare the welfare impact on consumer surplus between the two CAFE policies with and without attribute basing, I first simulate the equilibrium price without CAFE regulation. Following Barwick et al. (2017) [8], I use simulations to compare the welfare loss from the fuel economy regulations with and without the discrete attribute basing. I draw 10,000 random idiosyncratic preference vectors e_i from the Type 1 extreme value distribution for each consumer i. Conditional on each draw, I calculate the difference in the intrinsic utility between a consumers' private optimal choice and the policy-induced choice under each CAFE scenario. Let j^* denote the private optimal choice for consumer i with its intrinsic utility defined as:

$$u^0_{ij^*} = \max_{j=0,\ldots,J}\{\delta^0_j + \mu^0_{ij} + \epsilon_{ij}\} \tag{3.10}$$

where δ^0_j and μ^0_{ij} are evaluated at the price level under the no CAFE scenario. Suppose consumer i chooses vehicle model g instead of j^* under the CAFE policy such that:

$$u_{ig}^1 = \max_{j=0,\ldots,J}\{\delta_j^1 + \mu_{ij}^1 + \epsilon_{ij}\} \tag{3.11}$$

where δ_j and μ_{ij} are evaluated at the price level with CAFE. The monetized welfare loss for consumer i is defined as the difference in the intrinsic utility between the private optimal choice $j*$ with the choice g made under CAFE, divided by consumer i's price sensitivity:

$$\Delta CS_i = (u_{ij^*}^0 - u_{ig}^0)/\frac{\partial u_{ij}}{\partial p_j}, \quad g \neq j^* \tag{3.12}$$

When consumer does not change their optimal choice with the CAFE policy, the change in consumer surplus is the welfare loss (gain) from the implicit tax or subsidy he or she receives:

$$\Delta CS_i = (-\alpha_1(lnP_{j^*}^1 - lnP_{j*}^0) + \frac{\alpha_2}{Y_i}(lnP_{j^*}^1 - lnP_{j^*}^0))/\frac{\partial u_{ij}}{\partial p_j}, \quad g = j^* \tag{3.13}$$

where $P_{j^*}^0$ and P_{j*}^1 are the prices for the optimal vehicle choice j^* under the no policy and CAFE policy scenarios respectively. The above consumer surplus change is evaluated for each ϵ_i draw and then averaged across all draws to obtain the welfare loss (gain) for consumer i. The total welfare loss due to policy is obtained by averaging the individual welfare changes and multiplied with the total market size.

A policy would result in a higher consumer welfare loss if it makes more people to choose a model that deviates from their private optimal choice. The simulation results suggest that the current CAFE with discrete attribute basing costs $0.77 billion in consumer welfare while the CAFE policy removing the standard split results in a higher welfare loss, amounting to $1.75 billion. The uniform standard leads to a higher consumer welfare loss since the magnitude of the implicit tax/subsidy is larger due to a more stringent regulation, more likely to make consumers deviate from their private optimal choice. This finding is actually consistent with the implication from the theoretical illustration that the uniform standard incurs a higher compliance cost, reflected by the longer length of the compliance vector in Figure 3.5. Reynaert and Sallee (2017)[83] study the impact of firms' gaming in carbon emission standards for automobiles and find gaming in a binding fuel economy regulation could benefit consumers since it leads to lower prices by reducing firms' regulatory costs.[19] Analogously, the CAFE standards that feature the discrete attribute basing could reduce the compliance cost of automakers, especially the firms that produce a greater amount of light trucks, potentially benefit consumers through lower prices. However, the compliance burden measured by the loss in consumer private surplus needs to be evaluated against the social benefits from reduction in externalities that the policy intends to target. With a optimally-set policy standard, consumers would benefit more from the reduction in externalities than they loss in private surplus. Although the uniform standard leads to a larger consumer welfare loss, much of the policy-induced switching is not a

[19]Reynaert and Sallee (2017)[83] examine firms' manipulation of fuel economy ratings in the case of the carbon emissions regulation for automobiles in Europe. They find the implementation of aggressive carbon policies coincided with a significant decline of the accuracy of laboratory-based carbon emission ratings. They show that even gaming causes consumers to mis-optimize which leads to a loss in consumer surplus, it could benefit consumers through lower prices as gaming allows firms to reduce their costs.

distortion but an efficient change because it makes more consumers switch from the private optimal choice to the socially optimal choice by taking into consideration of the external costs of gasoline consumption. By allowing light trucks which generally emit more to receive a preferential treatment, the CAFE with attribute basing fails to make a consumer's vehicle choice achieve the socially optimal level. The relative subsidy for light trucks could even result in deviation from private optimum which is not efficient: consumers might choose vehicle models which are neither privately optimal nor socially optimal. In contrast, the uniform standard not only eliminates the loophole of implicitly subsidizing light trucks, but also encourages a consumer's vehicle choice towards the social optimum.

Firm Profits

Table 3.5 summarizes the impact of removing the discrete attribute basing on firms' profits. Removing the car-truck standard split decreases the total profits of domestic firms by 1.8% while the European and Asian enjoy a 4.0% and 1.5% boost in total profits respectively. The results imply that discrete attribute basing favors domestic firms at the expensive of foreign firms, which should not come as a surprise. Domestic firms have a disproportionately large share of vehicles that are classified as light trucks (Figure 3.11). The discrete attribute, which essentially provides a preferential treatment for light trucks, reduces the compliance burden for domestic firms. Asian firms, on the other hand, produce relative fuel-efficient vehicles. Even though they also have a relative large production presence in SUVs and vans in recent years, their fuel economy is higher and some are above the fuel economy targets. Asian firms also did not produce pickup trucks, which are normally dominated by domestic firms. European firms are hurt by the ABR the most due to their least production of light trucks. The changes in firm profits are also in line with the lobbying efforts by different firms. Asian firms have been advocating a more uniform standard while domestic firms tend to support the attribute-based standard.

On one hand, the car-truck standard split leads to a higher relative price of passenger cars, which puts cars into a position of disadvantage. On the other hand, by offering light trucks a less-stringent target, firms with a larger share of passenger cars also lose revenues from selling excess credits to firms who produce more light trucks and run a credit shortage. Table 3.5 also shows the total profit of the automobile industry increases, which might be surprising at first sight. Even though removing the attribute basing increases the stringency of the regulation and makes firms bear a large compliance burden, it makes fuel-efficient passenger cars such as electric vehicles, hybrid vehicles and some fuel-efficient small and mid-sized gasoline cars more affordable, attracting consumers who were not originally planning to purchase a new vehicle to buy those cars, increasing the market size of new vehicles.[20] The results imply that the implementation of the discrete attribute basing under CAFE deters the diffusion path of alternative fuel vehicle (AFVs) technologies. Due to the technology constraint such as the battery constraint, most of the alternative fuel vehicles are built on passenger car chassis. [21] The ABR puts passenger cars into a disadvantage and indirectly negatively impact the growth of the market size of alternative fuel vehicles. Especially during the early deployment stage of a new tech-

[20]As pointed in Section 3.6.2, small car buyers are more price sensitive than truck buyers and are more likely to switch between the outside option (public transportation and used cars) and new cars. It is expected that a uniform standard leads to a larger market size from an increasing number of new car buyers, more than offsetting the loss in the truck segment.

[21]By the end of May 2017, 12 out of the 13 BEV models are passenger cars, 16 out of the 21 PHEV models are passenger cars, and the only 3 hydrogen vehicles are all passenger cars.

nology, the car-truck standard split generates externalities in those AFV markets due to indirect network effects, and the total impact could be significantly large if taking into account of the feedback loops [70].[22]

Figure 3.10 presents the impact of removing ABR on the profits of a selected group of automakers covering different countries of origin. The heterogenous impact on different firms reflect important heterogeneity that arises from the differences in firm's product mix. Firms with a larger production share of fuel-efficient passenger cars are hurt by the attribute basing the most, while the firms with a larger production share of fuel-inefficient light trucks benefit more from ABR. With the removal of standard split between cars and trucks, domestic Big Three all experience a profit drop with Fiat-Chrysler suffering the largest profit decrease due to its largest production share of light trucks (about 70%). Ford and GM also maintain a relatively fuel-efficient passenger car fleet compared with Fiat-Chrysler, as shown in Figure 4.[23] With a uniform standard, the standard for passenger cars actually becomes looser while the standard for light trucks becomes more stringent. Many of the vehicles in the passenger car fleet of both Ford and GM generate abundant credits and their relative prices will be lower, attracting consumers who were originally planning to buy a light truck and who were not considering buying a new vehicle. The increase in profits from the passenger car fleet offsets part of the profit loss from the light truck segment. Fiat-Chrysler, on the other contrary, does not benefit much from the uniform standard due to their less-fuel efficient passenger car fleet, and thus the

[22]For example, a smaller number of EV sales would negatively impact the investment of charging stations, which would then further decrease the sales of EVs.

[23]Ford and GM are also more actively involved in the alternative fuel vehicle market. GM's Chevrolet Volt has been one of the most popular PHEV models. Ford has introduced many popular hybrid and PHEV vehicles including Ford Fusion Hybrid, Ford C-Max Hybrid, Ford C-Max Energi, and Ford Fusion Energi. The uniform CAFE standard will benefit the two firms from the increase in sales of those AFV models. Chrysler is not an active player in either the hybrid or the EV segment.

profit increase from its passenger car fleet is not able to offset much of the profit loss of their light truck fleet, leading to a larger profit loss. Tesla, which only produces EVs, benefits from the uniform standard by being able to generate more revenue from selling regulatory credits to other firms.

Among Asian firms, Toyota and Nissan experience a profit increase around 5%, while Honda suffers a profit loss about 0.6% from removing the discrete attribute basing. Even though Honda maintains a relatively fuel-efficient fleet for both passenger cars and light trucks, when the standard split is removed, the sales increase in the its passenger car fleet is not able to cover the profit loss from its light truck fleet, due to increased competition from Toyota and Nissan in the passenger car segment. Honda also has a higher production share of light trucks (40%) than Toyota (35%) and Nissan (29%) and thus suffer more compliance burden from the uniform standard (Figure 3.11). Among Asian firms, Honda is also considered as one of the "laggards" in electric vehicle industry with its minimum effort in investing EVs [82]. Therefore, with a more stringent regulation, Honda is not able to rely on EVs to generate more credits as other automakers who lead the EV market. The European firms, however, all experience a profit increase due to their larger investment in passenger cars and the least production share of light trucks (about 20%). Combining Figure 3.10 and Figure 3.11 reveals a general pattern that the distributional effects of the discrete attribute basing is highly correlated with the production share of light trucks: firms with a larger light truck fleet suffer more from the removal of attribute basing.

The empirical findings here are consistent with Ito and Sallee (2016)[52] that attribute basing could achieve redistribution if policy makers want to shift welfare across producers based on the secondary attribute. The CAFE regulators could use the car-truck standard split to redistribute producer surplus from foreign firms to domestic firms who produce a larger share of less fuel-efficient light trucks. However, the benefits of the distributional goals, possibly protectionism, should be evaluated against the potential welfare loss due to the distortion from the secondary attribute. When policy makers are designing the optimal standard difference, they should balance between maximizing the distributional goals (which requires an increase in the standard gap) and minimizing the welfare loss from the distortion in the secondary attribute (which requires a reduction in the standard gap).

ABR also decreases the vehicle market size by discouraging some consumers from buying new vehicles. Those consumers would then switch to the outside option by buying a used car or choosing public transportation. The implementation of ABR thus results in a redistribution of producer surplus across industries from the substitution to the outside option. Evaluating the impact of ABR across industries is beyond the scope of this paper and this study will evaluate the welfare impact within the automobile industry without taking account of the cross-industry profit redistribution.

Externalities

As indicated in the graphic illustration of Figure 3.5, the attribute basing results in a decrease in emission reduction and an increase in the market share of light trucks. Therefore, removing the car-truck standard split will reduce both the emission level and the sales of light trucks. A uniform standard will result in a market share of light trucks that is even smaller than the level in a no-regulation scenario. However, this is an efficient change rather than a distortion, reflecting that consumers internalize the externalities of gasoline consumption when choosing between a passenger car and a light truck.

Simulation results show that unifying the standards results in total reductions in vehicle lifetime gasoline consumption up to 1.61 billion gallons (or a 1.92% decrease) and CO_2 emissions up to 14.9 million metric tons over vehicle lifetime for the vehicles sold in 2014. The total external costs that could be saved from this reduction in CO_2 emissions by switching from the ABR to a uniform standard are estimated to be \$0.54 billion. Through burning petroleum, vehicle use also generates certain criteria air pollutants, including volatile organic compounds (VOC), nitrogen oxides(NO_x), fine particulate matter ($PM_{2.5}$), and sulfur dioxide (SO_x). The consumption of petroleum products also increases the external costs associated with dependence on oil imports. To quantify the economic value of reduction in criteria air pollutants and oil imports, I connect the changes of the fleet composition due to the uniform standards with the external costs associated with one gallon of gasoline usage using the estimates adopted by NHTSA in evaluating the environmental benefits of CAFE standards, converted to 2014 dollars adjusting for inflation. The parameter values and sources are reported in Table 3.7 and the external cost savings from the removal of the discrete attribute basing are reported in Table 3.6. All of the numbers of externality savings reflect total vehicle lifetime changes from annual sales and are discounted to the model year 2014.[24]

It is worthwhile noting the caveats underlying those estimates. First, the

[24]EPA assumes the total vehicle lifetime mileage to be 195,264 for passenger cars and 225,865 for light trucks. I assume a vehicle lifetime of 15 years for both passenger cars and light trucks and an annual mileage of 13,018 and 15,058 respectively. The annual discount rate is assumed to be 5%.

lifetime VMT is assumed to be fixed under the two CAFE scenarios. Under the uniform standard, consumers choose the fuel efficiency level higher than in the ABR, which could induce them to drive more due to the decreased cost of driving per mile for a given gasoline price, resulting in the rebound effects, which could undermine the policy gain from a more stringent CAFE. However, stricter fuel economy regulations encourage consumers to choose smaller and lower-performance vehicles, which reduces the marginal benefits of driving per mile. Thus, the rebound effects could be weakened by shrinking car size and the net response of miles could be zero or negative [4, 95]. Second, the outside option is assumed not to consume any gasoline. In reality, all the other transportation methods (subway, buses, biking...) are lumped into the outside option with each consuming different levels of gasoline. Assessing the substitution with each of the alternative transportation mode in the outside option and evaluate the respective gasoline consumption change is beyond the scope of this paper. The simulation results show that removing the discrete attribute basing makes some consumers switch from the outside option to new cars, and assuming that the outside option does not consume gasoline would underestimate the gasoline savings from the uniform standard by the amount equaling to the total gasoline consumption from the outside choices.

Basing the stringency of the regulation on a secondary attribute is likely to create a undesirable byproduct if the distortion in the secondary attribute is related to an unwanted outcome or another externalitity that regulation does not intend to target. In addition to having a higher weight than passenger cars that impose greater risks to victims in a collision, light trucks are constructed to be taller implying a higher probability of hitting the head or the upper body of other road users. Light trucks also have stiffer frames that transfer more force to the victims, resulting in a higher probability of fatality [41, 97, 78, 3, 2]. Consumers buy light trucks as a precautionary measure to protect themselves in a multi-vehicle collisions, while creating an externality to other road users due to a greater danger that light trucks impose to both other light trucks and passenger cars. This kind of "arms race" results in market share of light trucks larger than the socially optimal level [69]. The differential treatment of passenger cars and light trucks under CAFE not only fails to correct for this externality, but exacerbates the externality by implicitly subsidizing light trucks and creating additional policy-induced distortion. By estimating consumer's preference for reduced fatality risk in vehicle collisions, or the value of a statistical life (VSL), Li (2012)[69] estimates that the accident externality imposed by a light truck during a 10-year discounted vehicle life time is equal to $2,444 in 2006. By updating parameters using 2014 market conditions, the accident-related externalitity is estimated to be $2,701 in 2014 dollars. The discrete attribute basing leads to an additional sales of 354,269 in light trucks. One back-of-the-envelop estimate implies that the increase in light trucks leads to a welfare loss of $0.96 billion. However, the uniform standard that removes the standard split between cars and trucks makes the fuel-efficient passenger cars more affordable, increasing the market size of new vehicles. Part of the external cost savings from fewer light trucks are offset by the increased automobile usage. To take account of this effect, the external cost of increased accidents from the additional cars[25] are subtracted from the accident externality savings from the uniform standard by assuming all the consumers who switch from the outside option to new cars were not planning to buy any vehicle. The resulting net-savings in accident externalities from the uniform standard is estimated to be $0.42 billion.

[25]The value of accident-related external cost from additional cars used for calculating accident externality savings from a uniform standard is reported in Table 3.7.

This estimate provided here is relatively crude, which does not take account of the heterogeneity of the risks imposed by the vehicles within the light truck segment. A more accurate estimate would require a more detailed estimate of the additional probability of fatality that light trucks impose in a multi-vehicle collision for each of the light truck model, which currently is unavailable. The externality estimate here also does not include the externality that light trucks impose to road users other than vehicle occupants.

Figure 3.12 summaries the findings of the welfare consequences discussed above. Compared with the ABR, although a uniform standard results in larger loss in consumer surplus by making more consumers' choices deviate from the private optima, the changes are rather efficient, resulting in a larger firm profit, and larger savings in external costs related to gasoline consumption and vehicle accidents, and eventually a net social welfare improvement up to \$2.83 billion in MY 2014.

3.6 Conclusion

This paper investigates the welfare consequences of attribute basing on a discrete characteristic in the context of U.S. fuel economy regulation. Through a structural model of vehicle demand and supply, I run simulations of removing the standard split between passenger cars and light trucks and find that the discrete attribute basing raises the sales of light trucks by 4.9% and reduces the sales of passenger cars by 8.0%. The policy-induced sales increase of light trucks leads to increase of externalities associated with vehicle-lifetime pollutant emissions, carbon emissions, and oil imports amounting to \$1.09 billion.

Due to the structural difference of light trucks, the favorable treatment of light trucks also results in an increase in accident-related externalities equivalent to \$0.42 billion. Although the uniform standard results in a larger deviation in vehicle choice away from consumer's private optimum, much of the change is actually efficient and the uniform standard dominates the attribute basing policy by \$2.83 billion in social welfare taking into account consumer surplus, firm profits and externalities. ABR redistributes producer surplus between domestic and foreign firms: the car-truck standard split increases the profits of domestic firms by 1.8% and reduces the profits of Asian and European firms by 1.5% and 4.0% respectively. However, the benefit of favoring domestic firms should be evaluated against the additional distortionary cost induced by the discrete attribute basing. Since most of alternative fuel vehicles are built on a passenger car chassis due to technology constraint, the standard split that puts passenger cars into disadvantage could potentially deter the diffusion of alternative fuel technologies and the negative impact could be multiplied due to the existence of indirect network effects. Results of this paper suggest that any political and distributional argument in favor of policy differentiation should be carefully evaluated against the significant distortions created by the difference in regulation stringency or policy incentive.

This paper has several limitations and motivates two lines of possible extensions. First, the vehicle supply framework is based on a static setup and assumes away credit banking and borrowing. Since my data sample covers MY 2012-14, a period when the fuel prices were quite stable and no significant demand shock occurred, the static solution of this study should approximate the dynamic solution when firms are allowed to carry credits backward or forward. Future work could model a firm's dynamic decision in maximizing profits from vehicle and credit sales by incorporating the credit banking feature to investigate the impact of attribute basing on the automobile industry in a longer horizon. Second, this study assumes that automakers choose only price to maximize profit from vehicle and compliance credit sales. However, automakers in reality employ the strategy that is the least costly and might apply a mixture of strategies to comply with the regulation. When the "sales-mix" strategy is rather expensive to adopt due to an increase in regulation stringency, automakers might seek alternative methods that result in lower compliance cost such as increasing fuel economy of existing models. Therefore, by restricting automakers to apply the "sales-mix" strategy, the results presented in this study would overestimate the policy impact from a more stringent standard. However, as long as the time horizon is short and the distribution of compliance burdens across fleets does not change, the qualitative findings in my study would remain. Further research that focuses on the long-term impact could estimate the distortionary cost of the discrete attribute basing by estimating the additional cost and resources that automakers put in designing light trucks to receive a more favorable regulatory treatment.

Table 3.1: Summary of Consumer Survey Data

	2012		2013		2014		All Years	
Variables	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev	Mean	Std.Dev
Household income (1,000$)	121.38	97.71	122.83	108.31	122.47	97.78	122.26	101.39
Houshold size	2.67	1.24	2.63	1.22	2.58	1.18	2.62	1.21
With a college degree	0.60	0.49	0.59	0.49	0.59	0.49	0.59	0.49
Living in an urban area	0.64	0.48	0.61	0.49	0.63	0.48	0.63	0.48
Average commuting time (mins)	25.61	5.96	25.57	5.83	25.47	5.88	25.54	5.89
Average gasoline price ($)	3.51	0.63	3.52	0.64	3.43	0.58	3.48	0.62
Average price of the purchased vehicle (1,000$)	28.89	12.98	29.66	13.68	30.44	13.97	29.71	13.58
Purchasing a light truck	0.48	0.50	0.50	0.50	0.52	0.50	0.50	0.50
Average MPG of the purchased vehicle	25.09	7.39	25.83	8.55	26.30	9.27	25.77	8.50
Observations	2784		3032		3259		9075	

Table 3.2: Parameter Estimates in Mean Utility

	(1) OLS		(2) IV	
	Coefficient	S.E.	Coefficient	S.E.
constant	8.1667	0.7080	6.3266	0.9295
log(price)	-1.2533	0.4987	-4.1081	1.0613
horsepower/weight	1.6455	0.7089	4.0015	1.0496
gallons/mile	1.6460	0.4862	1.2802	0.5161
weight	1.0295	0.2606	1.0167	0.2731
AFV dummy	-2.5336	1.0462	-3.0228	1.1280
van dummy	-0.1785	0.0323	-0.2166	0.0349
pickup dummy	-5.4737	0.5096	-5.3216	0.4880
SUV dummy	-0.8165	0.6849	1.4264	1.0017
model year 13 dummy	2.0349	0.1206	2.0104	0.1270
model year 14 dummy	1.5426	0.1031	1.5100	0.1050

Table 3.3: Parameters Estimates in Heterogeneity Component

	Coefficient	S.E.
Observed Heterogeneity		
log(price)/income	-13.2672	0.6879
urban*pickups	-0.6819	0.0799
urban*afv	0.4064	0.1014
family size*vehicle weight	0.1067	0.0345
gasoline price*gallons/mile	-0.0747	0.0221
Random coefficients		
gallons/mile	0.3858	0.0136
horsepower/weight	5.2485	0.1690
light trucks	2.8224	0.2537
Own-price Elasticity	-5.51	

Note: the number of observations are 9075. log-likelihood at convergence: -94215.03. 150 Halton draws are used for simulating the unobserved heterogeneity. The instrument variables used to estimate the linear parameters are the difference and squared difference in characteristics with other products in the same firm and in other firms.

Table 3.4: Market Outcomes of a Uniform Standard

Segment	No.of Models	Average Price($)	Price Change ($)	Sales in 2014	Sales Change
cars	260	29,745	-471.0	6,264,019	8.0%
suvs	147	36,773	2215.9	4,736,461	-1.5%
vans	14	27,382	2988.7	106,266	-12.2%
pickup trucks	38	40,622	4317.2	1,780,584	-11.9%
light trucks	199	38,270	2766.2	6,623,311	-4.9%

Note: the average prices reported are sales-weighted. The price changes are sales-weighted average price changes per model, summarized by segment.

Table 3.5: Firm Profit Impact from Removing Attribute Basing

Firms	Profit Change (%)
Domestic	-1.77
European	4.03
Asian	1.53
Total	0.89

Table 3.6: Welfare Consequences of Removing Attribute Basing

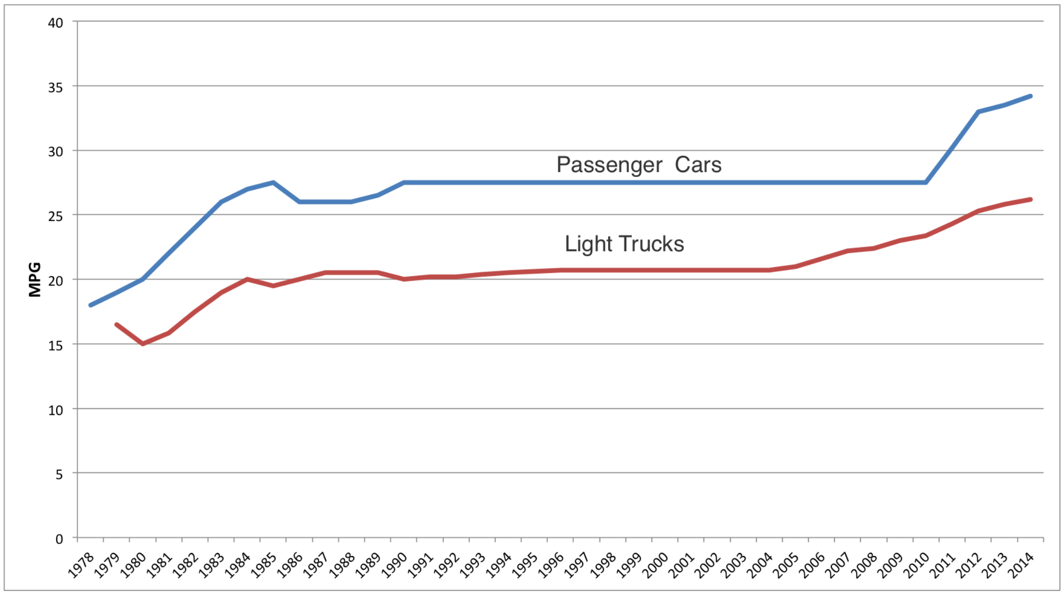
Welfare	billion $
Δ Consumer surplus	-0.98
Δ Firm profit	2.30
Δ Pollutant emission externality savings	0.24
Δ GHG emission externality savings	0.54
Δ Oil imports externality savings	0.31
Δ Accident externality savings	0.42
Δ Total social welfare	2.83

Note: the external cost savings are vehicle lifetime savings discounted to year 2014. Pollutant emission externality savings include VOC, NO_x, $PM_{2.5}$ and SO_2. The parameters used for external cost calculation are reported in Table 3.7.

Table 3.7: Parameters for External Cost Calculation

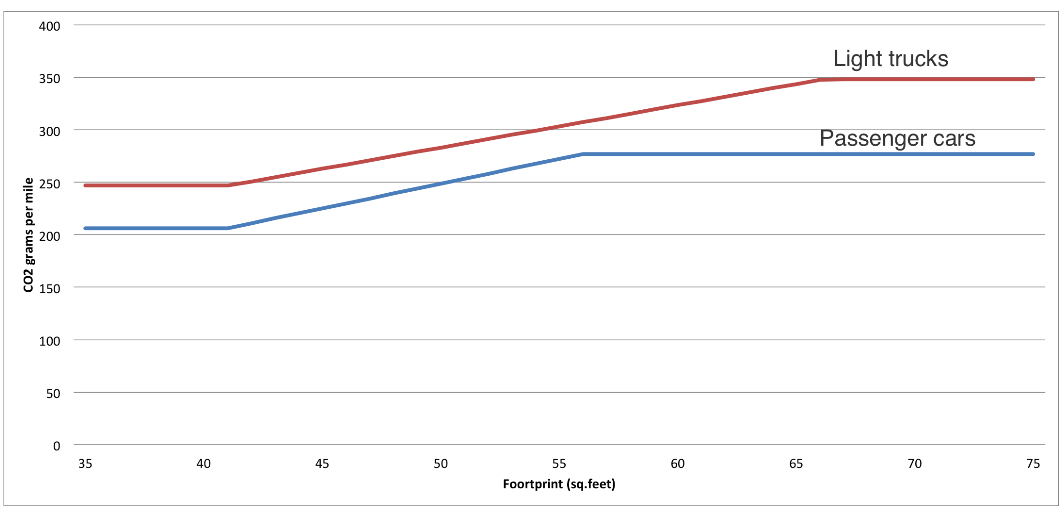
Parameters	Value	Source
Discount rate	5%	
Lifetime VMT for cars	195,264	EPA (2014) [34]
Lifetime VMT for trucks	225,865	EPA (2014) [34]
Emission rates	grams/gallon	
VOC	24.9	EPA (2008)[32]
NO_x	16.7	EPA (2008) [32]
$PM_{2.5}$	0.1	EPA (2008) [32]
SO_2	0.17	EPA (2008)[32]
Emission damage costs	$/ton (2014 value)	
VOC	1,482	NHTSA (2010) [77]
NO_x	6,042	NHTSA (2010) [77]
$PM_{2.5}$	330,600	NHTSA (2010)[77]
SO_2	35,340	NHTSA (2010)[77]
CO_2	36	EPA (2016) [35]
External cost of oil imports ($/gallon)	0.17	EPA (2008) [32]
External cost of additional light truck ($/ unit)	2,444	Li (2012) [69]
External cost of additionl car ($/mile)	0.026	NHTSA (2010) [77]

Figure 3.1: Historic CAFE standard split between passenger cars and light trucks



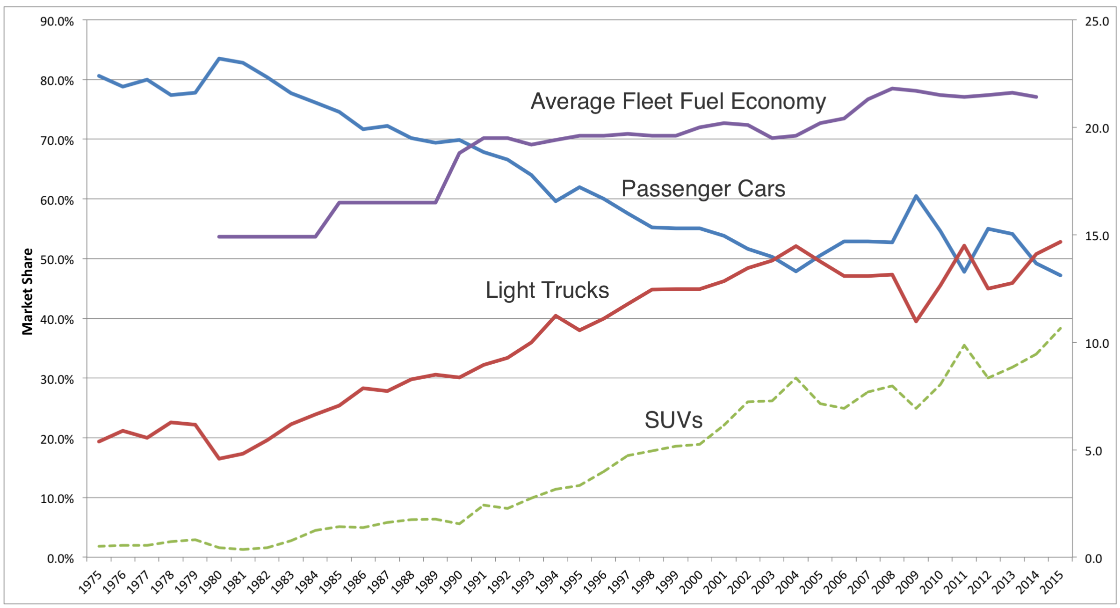
Data source: U.S. Department of Transportation

Figure 3.2: GHG emission standard split for passenger cars and light trucks in MY 2016



Data source: Light-Duty Vehcile Greenhouse Gas Emission Standards and Corporate Average Fuel Economy Standards; Final Rule. May 2010.

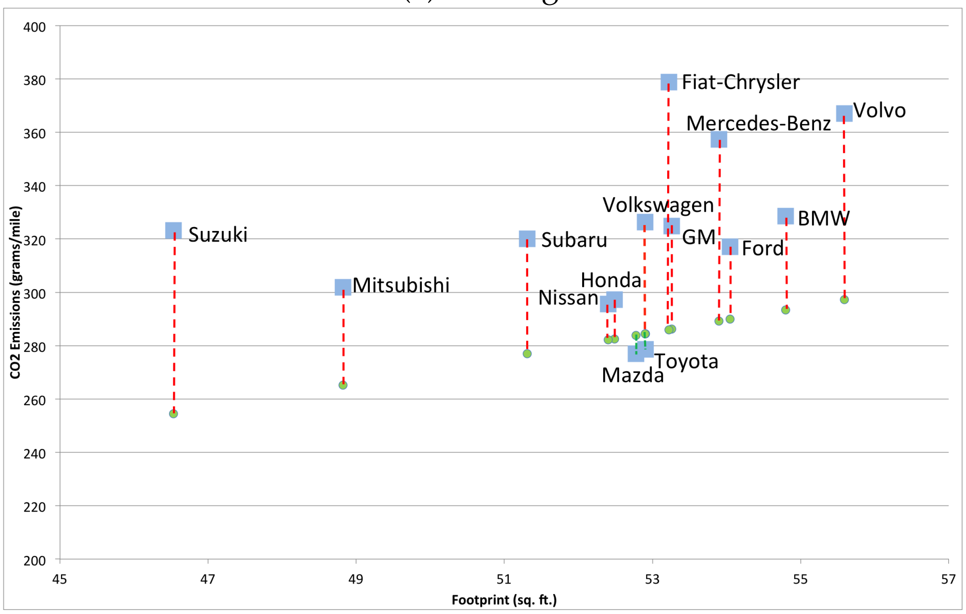
Figure 3.3: Annual market share of passenger cars and light trucks in the U.S.



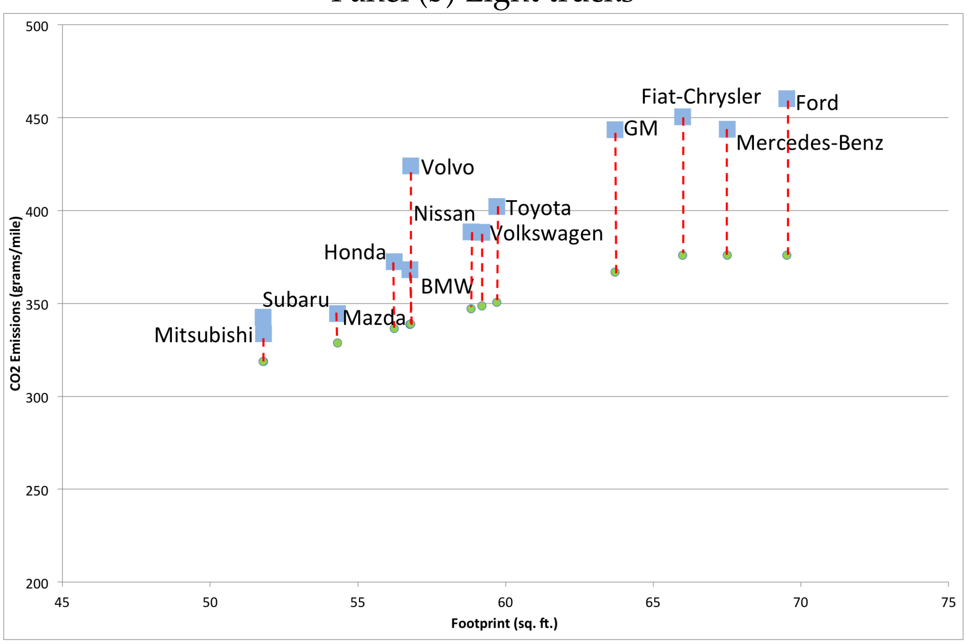
Data source: data on market shares of passenger cars and light trucks are from Ward's Automotive Reports, and data on annual average fleet fuel economy from 1980 to 2015 are obtained from U.S. Bureau of Transportation Statistics.

Figure 3.4: GHG emission targets and actual fleet-average emissions

Panel (a) Passenger cars



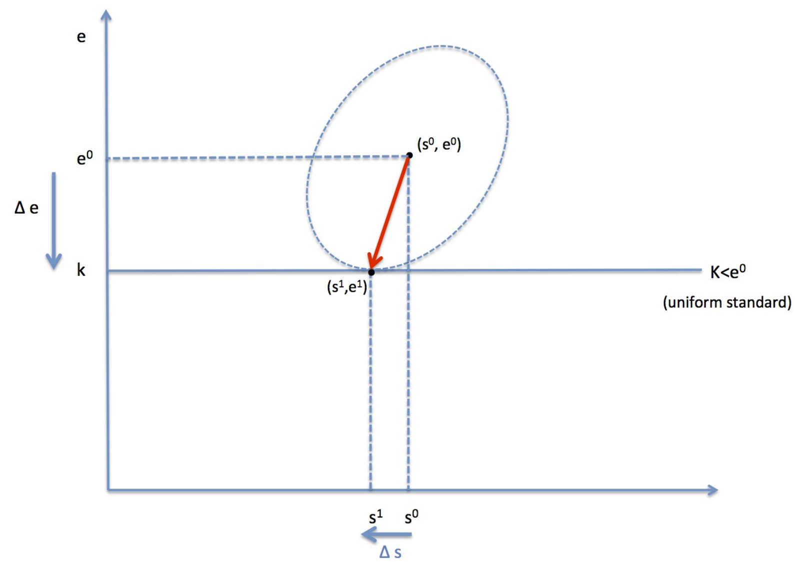
Panel (b) Light trucks



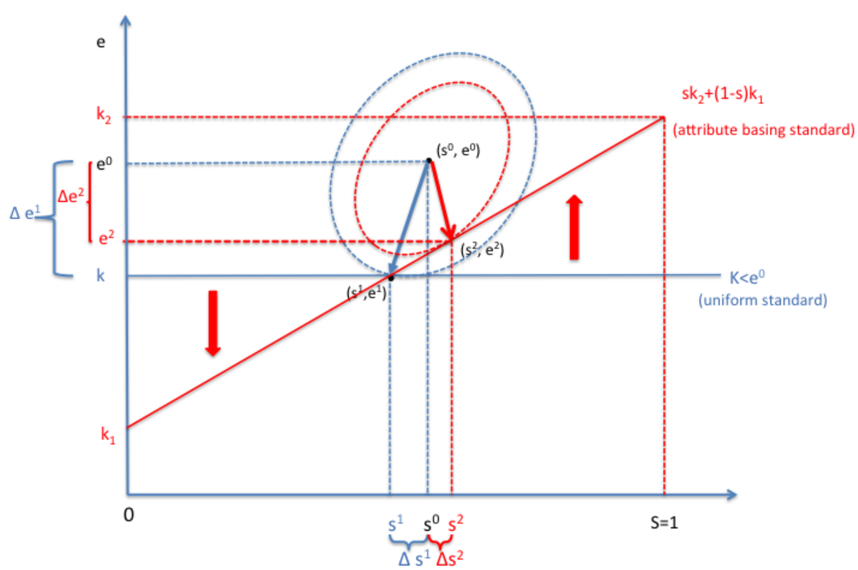
Note: The blue squares represent the sales-weighted average emission per mile. The green dots represent the GHG emission standard targets for the corresponding footprint level.

Figure 3.5: Graphic illustration of discrete attribute basing

Panel (a) Uniform Standard



Panel (b) Discrete Attribute Basing



Note: the horizontal axis represents the market share of light trucks (s), while the vertical axis represents the emission level (e). The uniform standard assigns an emission mandate at k. The policy of discrete attribute basing assigns a standard k_1 for passenger cars and k_2 for light trucks.

Figure 3.6: Own-price elasticity estimates

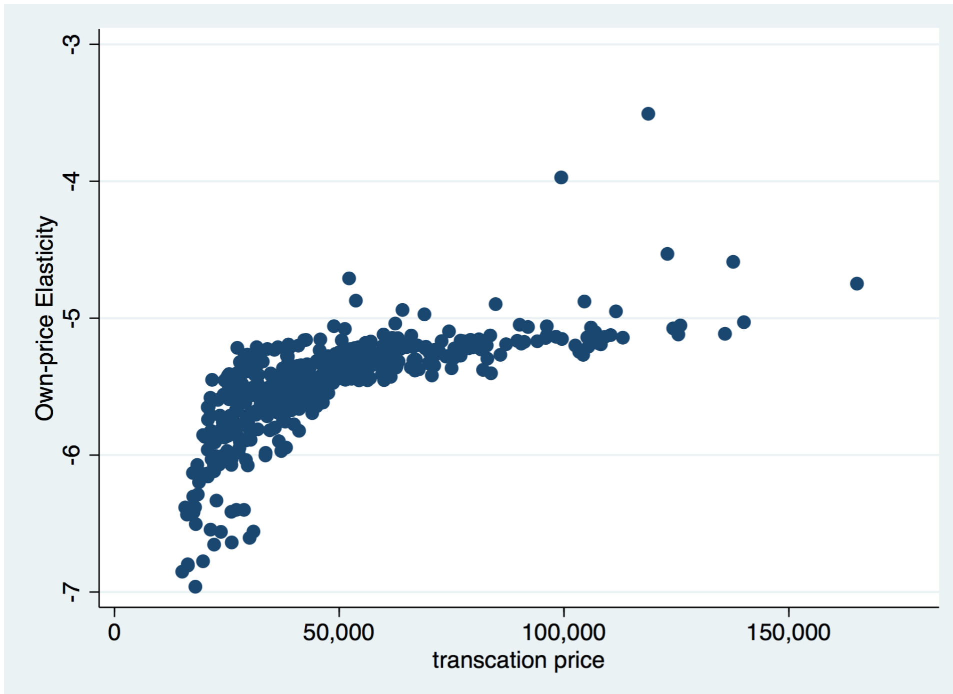


Figure 3.7: Estimates of price-cost margins

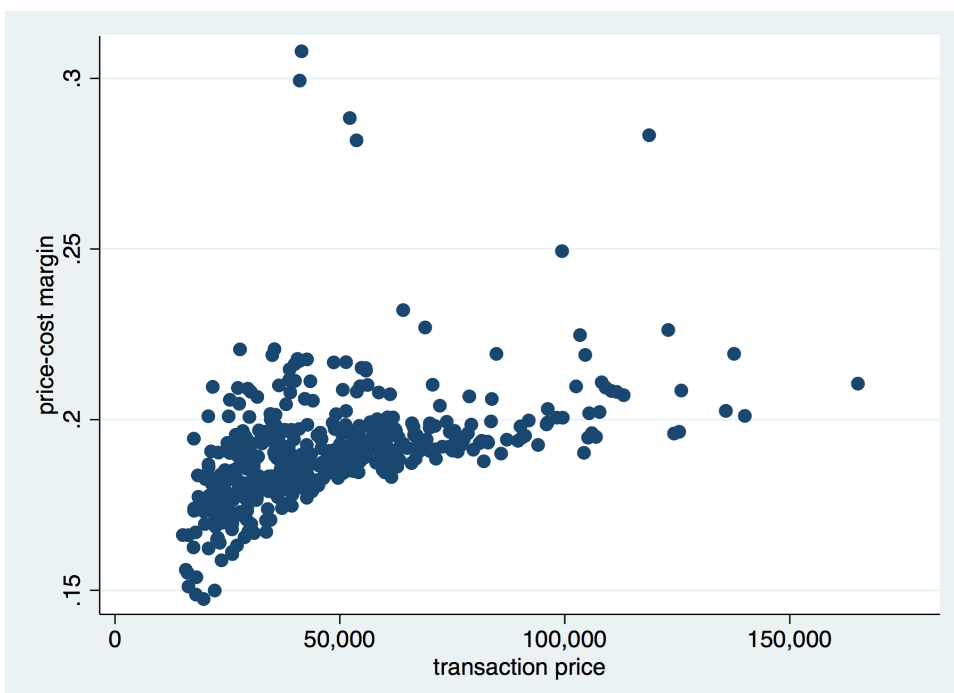
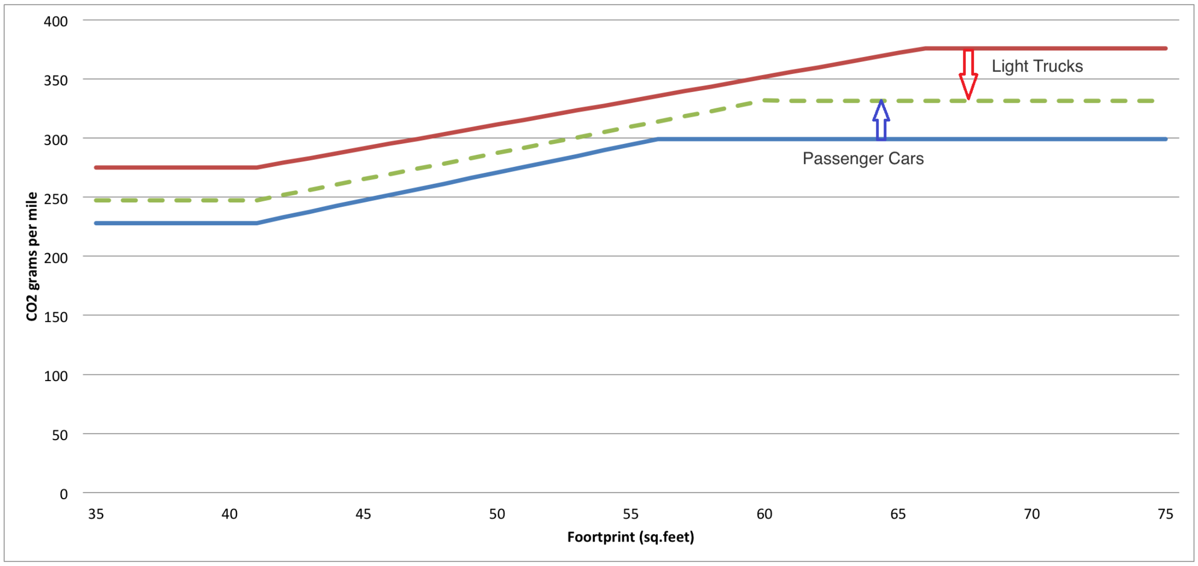


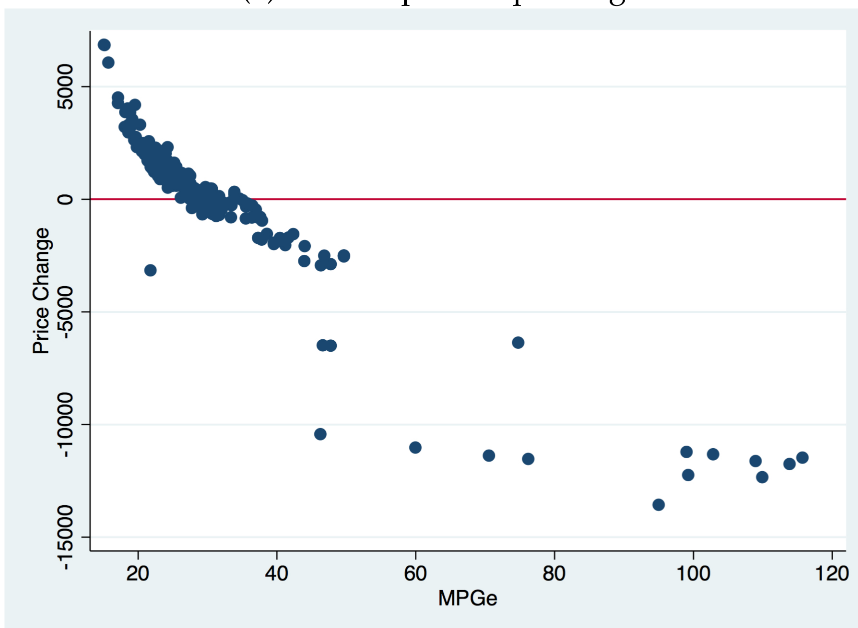
Figure 3.8: Uniform footprint-based standards for MY 2014



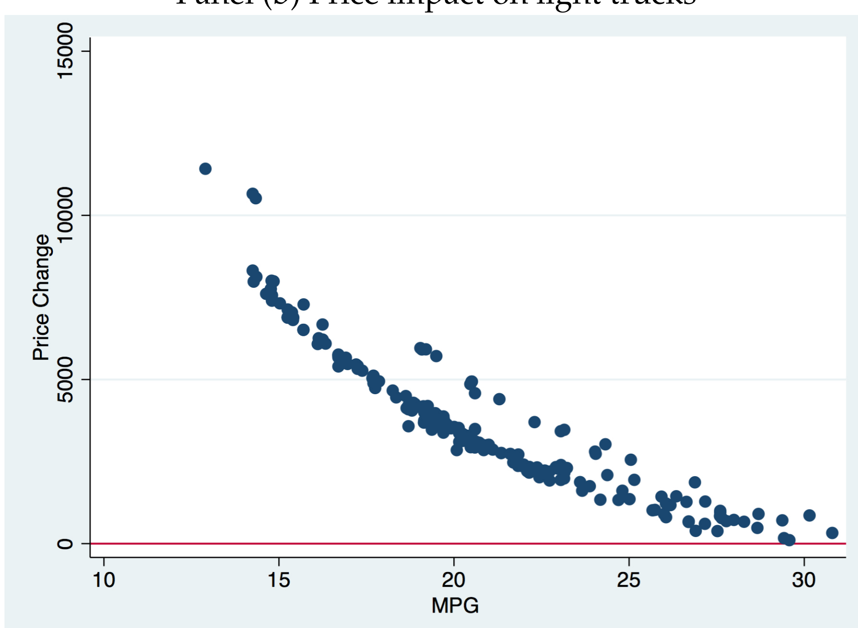
Note: the uniform footprint-based standards use the sales-weighted average parameters of the passenger car and light truck fleets for the emission standard formula.

Figure 3.9: Price changes due to removal of attribute basing

Panel (a) Price impact on passenger cars



Panel (b) Price impact on light trucks



Note: the figure plots the price changes due to the removal of the car and truck standard split.

Figure 3.10: Firm profit changes due to removal of attribute basing

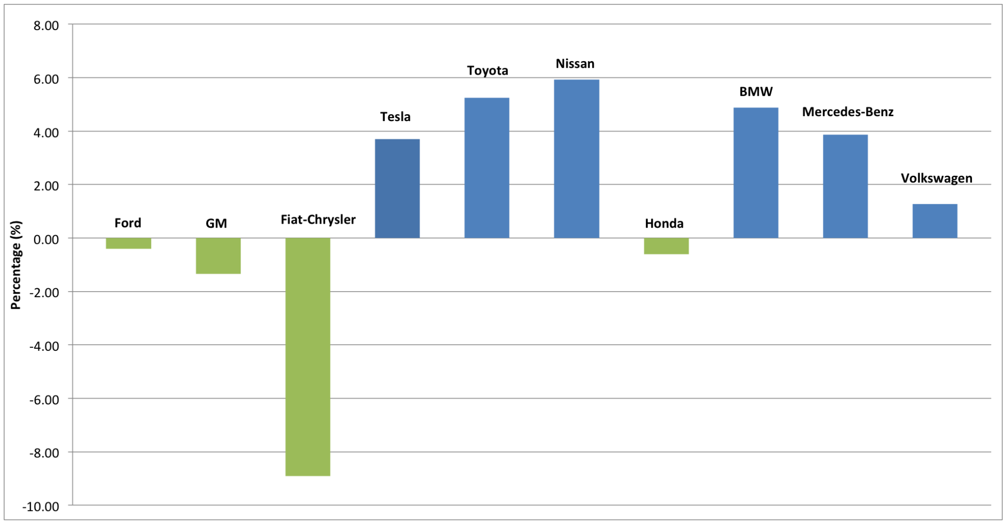


Figure 3.11: Production share of light trucks in MY 2014

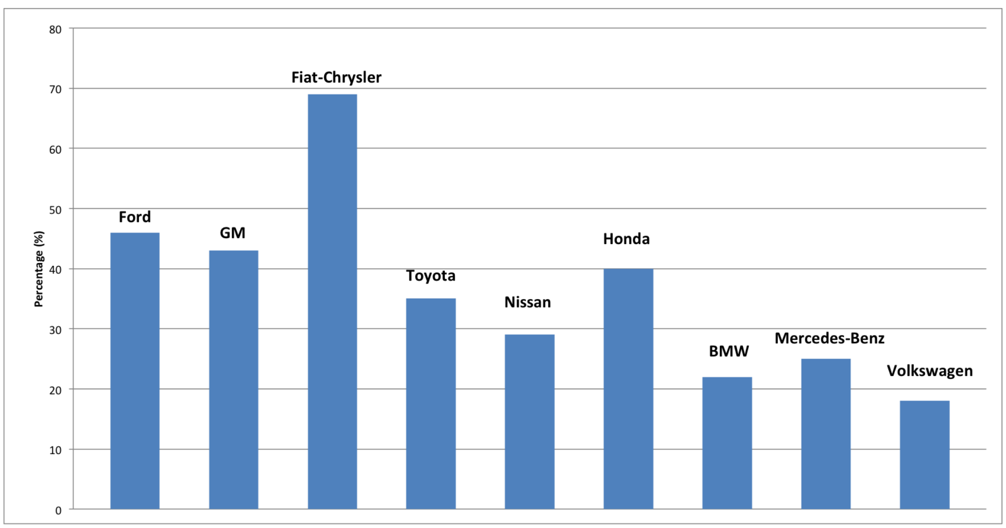
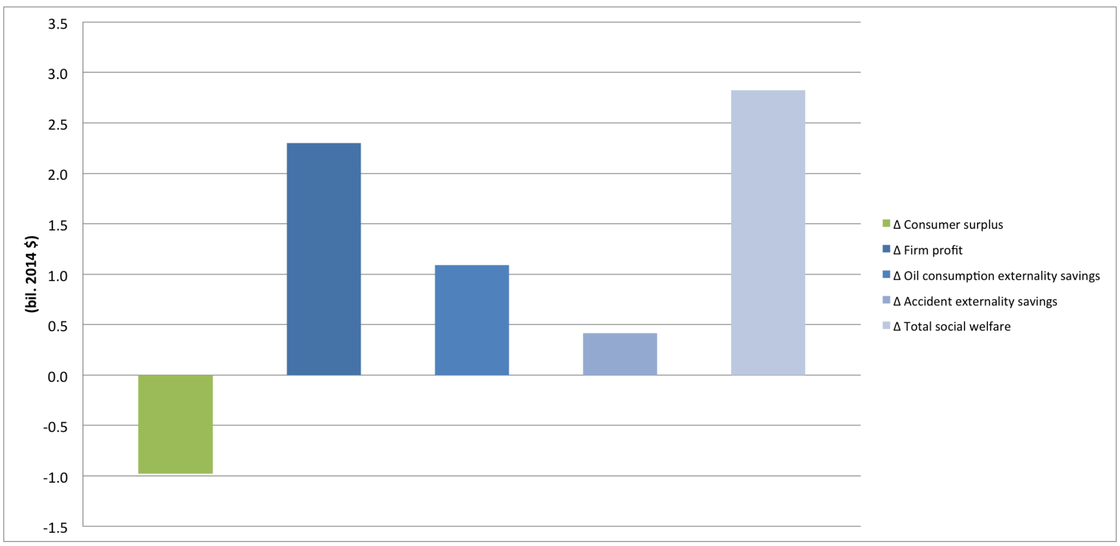


Figure 3.12: Welfare changes by removing the discrete attribute basing



Note: The figure shows the welfare impacts from removing the attribute basing. All the welfare changes are capitalized to 2014 $ and are recorded in billion $. Oil consumption externality savings include savings of external costs from air pollutant emissions, CO_2 emissions and oil imports.

APPENDIX A

ENTRY MODEL OF CHARGING STATIONS

The entry model is developed based on [40]. Denote EV owners' demand for charging station j by $D(p_1, ..., p_N)$, where N is the number of charging stations available in a given market, and p_j is the price at charging station j, $j = 1, ..., N$. We assume that demands are symmetric in terms of prices at different charging stations. Furthermore, we assume that the marginal cost is constant, denoted by c, and that the profit function from each EV owner $(p_j - c)D(p_1, ..., p_N)$ is quasi-concave in p_j. Under these assumptions, there exists an equilibrium in which all stations charge the same price which depends on N, denoted by $p(N)$. Denote the equilibrium markup by $\varphi(N)(\equiv -\frac{D(p)}{[\frac{\partial D(p)}{\partial p}]})$ and assume $\varphi'(N) < 0$, which is consistent with most common competition models. Let $f(N) = \varphi(N)D(p(N))/N$. Then the per-period profit of a station in market m at time t is $\pi_{mt} = Q_{mt}^{EV} f(N_{mt})$.

Now consider a charging station's entry decision. If a charging station enters market m at time t, it pays the entry cost F_{mt} and earns the profit streams $(\pi_{mt}, \pi_{(mt+1)}...)$, generating a discounted profit of $-F_{mt} + \pi_{mt} + \delta\pi_{mt+1} + ...$, where δ is a discount factor common to all stations. If a station enters market m at time $t+1$, it generates a discounted profit of $-\delta F_{mt+1} + \delta\pi_{mt+1} + \delta^2\pi_{mt+2}....$ In a free-entry equilibrium firms must be indifferent between these two options. This implies

$$F_{mt} - \delta F_{mt+1} = \pi_{mt} = Q_{mt}^{EV} f(N_{mt}).$$

Taking the natural logarithms of both sides, we can get

$$ln(F_{mt} - \delta F_{mt+1}) = ln(f(N_{mt})) + ln(Q_{mt}^{EV}) \quad \text{(A.1)}$$

We specify the entry cost as

$$ln(F_{mt} - \delta F_{mt+1}) = \rho_0 + \rho_1 Z_{mt} + \tau_{mt}, \tag{A.2}$$

where τ_{mt} is the unobserved entry cost, and the vector of covariates Z_{mt} includes the state-level tax credit given to charging station investors measured as the percentage of the building cost, a dummy variable indicating whether there exists public grants or funding to building charging infrastructure, the interaction term of number of grocery stores in a MSA in 2012 with the lagged number of charging stations in all MSAs other than own (the instrument in the EV demand equation), and other control variables.

We specify the profitability of charging station $f(N)$ as follows

$$ln(f(N_{mt})) = \lambda_0 + \lambda_1 ln(Q^{EV}_{mt}) + \vartheta_{mt}, \tag{A.3}$$

where N_{mt} is installed base of charging stations by time t which captures the competition among charging stations, and ϑ_{mt} is an error term that captures the unobserved local demand shocks.

Furthermore, we decompose the local shock as

$$(\tau_{mt} - \vartheta_{mt})/\lambda_1 = T_t + \varphi_m + \varsigma_{mt}, \tag{A.4}$$

where T_t is year-quarter dummies that control for time effects common to all the MSAs, φ_m is market fixed effects that control for time-invariant and MSA-specific preferences for charging stations, and ς_{mt} is an term capturing those idiosyncratic local demand shocks.

From equations (A.1), (A.2), (A.3), and (A.4), we can obtain the charging station equation (1.5) in Section 4.2:

$$ln(N_{mt}) = \gamma_0 + \gamma_1 ln(Q^{EV}_{mt}) + \gamma_2 Z_{mt} + T_t + \varphi_m + \varsigma_{mt},$$

where $\gamma_0 = (\rho_0 - \lambda_0)/\lambda_1, \gamma_1 = -1/\lambda_1, \gamma_2 = \rho_1/\lambda_1$.

APPENDIX B

PROOF OF PROPOSITION 1

Proposition 1: *Where there is compliance trading and the only regulatory goal is to target the emission externality with no distributional considerations, the optimal policy should have a uniform standard such that*:

$$\sigma^* = 0.$$

The regulator maximize the welfare W, which is sum of the expected utility from vehicle purchase and expected revenue from noncompliance fines less the expected external cost from vehicle emissions, by choosing the policy parameters k, σ and t:

$$\max_{k,\sigma,t} W = \mu ln(exp(V_c/\mu) + (exp(V_t/\mu)) + t((1-s)(e_c - k) + s(e_t - k - \sigma)) - \delta((1-s)e_c + se_t)$$

To ease exposition, denote the following three terms as the expected consumer utility, the revenue from noncompliance punishment, and the externality from emissions respectively:

$$V = \mu ln(exp(V_c/\mu) + (exp(V_t/\mu))$$

$$T = t((1-s)(e_c - k) + s(e_t - k - \sigma))$$

$$E = \delta((1-s)e_c + se_t)$$

First note that $\frac{\partial V_c}{\partial \sigma} = \frac{\mathscr{L}_c}{\partial \sigma} = 0$, $\frac{\partial V_t}{\partial \sigma} = \frac{\mathscr{L}_t}{\partial \sigma} = \sigma$ by the envelop theorem. The optimal value for the standard difference σ^* could be found by setting the first order condition of W with respect to σ equaling to zero. The first order conditions of the three terms with respect to σ are:

$$\begin{aligned}\frac{\partial V}{\partial \sigma} &= \mu \frac{\frac{1}{\mu} exp(V_c/\mu)\frac{\partial V_c}{\partial \sigma} + \frac{1}{\mu}(exp(V_t/\mu))\frac{\partial V_t}{\partial \sigma}}{(exp(V_c/\mu) + (exp(V_t/\mu))} \\ &= \frac{exp(V_t/\mu)\lambda}{(exp(V_c/\mu) + (exp(V_t/\mu))} \\ &= s\lambda\end{aligned}$$

$$\begin{aligned}\frac{\partial T}{\partial \sigma} &= t[\frac{\partial(1-s)}{\partial \sigma}(e_c - k) + (1-s)\frac{\partial(e_c - k)}{\partial \sigma} + \frac{\partial s}{\partial \sigma}(e_t - k - \sigma) + s\frac{\partial(e_t - k - \sigma)}{\partial \sigma}] \\ &= t[-\frac{\partial s}{\partial \sigma}(e_c - k) + \frac{\partial s}{\partial \sigma}(e_t - k - \sigma) + s(\frac{\partial e_t}{\partial \sigma} - 1)] \\ &= t\frac{\partial s}{\partial \sigma}(e_t - e_c) - t\frac{\partial s}{\partial \sigma}\sigma + ts\frac{\partial e_t}{\partial \sigma} - ts\end{aligned}$$

$$\begin{aligned}\frac{\partial E}{\partial \sigma} &= \delta[\frac{\partial(1-s)}{\partial \sigma}e_c + (1-s)\frac{\partial e_c}{\partial \sigma} + \frac{\partial s}{\partial \sigma}e_t + s\frac{\partial e_t}{\partial \sigma}] \\ &= \delta[-\frac{\partial s}{\partial \sigma}e_c + \frac{\partial s}{\partial \sigma}e_t + s\frac{\partial e_t}{\partial \sigma}] \\ &= \delta\frac{\partial s}{\partial \sigma}(e_t - e_c) + \delta s\frac{\partial e_t}{\partial \sigma}\end{aligned}$$

Therefore the first order condition of w with respect to σ is:

$$\begin{aligned}\frac{\partial W}{\partial \sigma} &= \frac{\partial V}{\partial \sigma} + \frac{\partial T}{\partial \sigma} - \frac{\partial E}{\partial \sigma} \\ &= s\lambda + t\frac{\partial s}{\partial \sigma}(e_t - e_c) - t\frac{\partial s}{\partial \sigma}\sigma + ts\frac{\partial e_t}{\partial \sigma} - ts - \delta\frac{\partial s}{\partial \sigma}(e_t - e_c) - \delta s\frac{\partial e_t}{\partial \sigma}\end{aligned}$$

An optimal policy requires the regulator to set k^* such that the equilibrium regulatory credit price (or the marginal compliance cost) is equal to the marginal benefit of one unit of emission reduction δ: $\lambda = \delta$. The regulator is also going to set the fine payment for one unit of noncompliance at the same price of the regulatory credit. Otherwise, no firm would comply with regulation but voluntarily pays the fine. Therefore, an optimal regulation implies that $\lambda = t = \delta$. The above first order condition reduces to:

$$\frac{\partial W}{\partial \sigma} = -t\frac{\partial s}{\partial \sigma}\sigma$$

Setting the first order condition to zero and solving for σ gives:

$$\sigma^* = 0.$$

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